Angels and Demons: The Negative Effect of Employees' Angel Investments on Corporate Innovation

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Abstract

Does a firm benefit if its employees personally invest in start-ups? To answer this question, we exploit novel data, which link angel investors in the US with their employment history. A firm's economic value of patents decreases by 3% - 5% when its employees personally invest in start-ups. We establish causality with matching and instrumental variable regressions, which rely on quasi-exogenous competition in the early-stage financing market. The negative relationship is stronger for angel investors in innovation-related roles, if the start-ups are more time consuming, and for exploratory patents. Compared to other angel investors, angel investors employed at corporations have a positive impact on future innovation and success of their invested start-ups. Our results indicate that angel investors divert time and effort from their employers to their personal investments. We highlight a trade-off between the benefits of angel investors for start-ups and the costs for their employer.

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1. Introduction

Angel investors are central in our economy to finance innovation. The size of the angel investment market is estimated to be as large as the extensively studied venture capital market (OECD (2011)). Also, there are policy initiatives aimed to encourage angel investing (Denes et al. (2020)). While existing literature shows a positive impact of angel investors on their portfolio start-ups' success (Kerr et al. (2014); Lerner et al. (2018)), little is known about what role they play in the economy besides angel investing.

In our sample, around 25% of the observable universe of angel investors in the US are employed at publicly listed firms *alone*. Many prominent corporate executives (e.g. Jeff Bezos, Marc Beinoff, Marissa Mayer, Reid Hoffman) are angel investors. We refer to such individuals as *angel employees*. In our sample, angel employees are predominantly upper management and are usually employed in innovation-related roles such as product managers, or technical directors. A typical example of a job description is as follows: *"Technical lead on founding engineering team for Google AdSense, the fastest-growing business within Google in Google history. Co-authored patent for "Processing digitally hosted volumes"*.

We provide systematic evidence on the following research question: Do angel employees help or hinder innovation of their employer? On the one hand, angel employees could help their employer innovate. Research on corporate venture capital (CVC) documents that corporations directly invest in start-ups through their CVC arm for strategic purposes (Hellmann (2002), Dushnitsky and Lenox (2005), Ma (2020)). In our setting, however, we look at personal investments of corporations' employees and not at investments of a corporation. Angel employees might use their personal investments to acquire knowledge about the start-ups' existing and future innovative activities[1]. This can help angel employees to guide innovative efforts at their corporate employer.

On the other hand, angel employees could have a detrimental impact on corporate innovation. This is rooted in a standard principal-agent or multitask framework (Jensen and Meckling (1976), Holmstrom and Milgrom (1991)). Angel employees face a trade-off

[1]Indeed, previous research has shown that many angel investors obtain a board seat or act in an advisory role (Wallmeroth et al. (2018))

between exerting effort in the innovative activities of their employer and their personal investments. Angel employees might actively monitor (treat) their portfolio start-ups. This is because there are time intensive board meetings for follow-on financing rounds, an acquisition, or going public. Careful selection of investments might also involve time intensive scouting. Angel employees could thus divert scarce resources, namely time and effort, from their corporate employer to their personal investments. This trade-off is exacerbated by the long-run nature of angel investments and the potential to earn extra-ordinary returns (Wiltbank et al. (2009)).

We exploit novel data, which link angel investments to their employment history. We collect personal equity investments in US early-stage firms between 2001-2018 from Crunchbase which totals more than $70 Billion of early stage capital. We then obtain employment histories of angel investors in our sample from LinkedIn. Employees such as Jeff Bezos are unlikely to have a LinkedIn profile. Therefore, we manually collect data in order to mitigate a possible selection bias. Our variable of interest is the total number of angel investors employed at a firm. The company with most angel employees in our sample is Alphabet, with a total of 202 employees who personally invested across 414 start-ups between 2001 and 2018.

We find that the number of angel employees at a firm is negatively correlated with corporate innovation. The effect is statistically significant and economically meaningful. The presence of angel employees correlates with a reduction of future economic value of patents of 3%. This inference holds when we measure innovation as the economic value of patents (Kogan et al. (2017)) or as truncation-adjusted citation-weighted patents (Hall et al. (2005)). We include a host of controls as well as firm and year fixed effects or alternatively industry-year fixed effects. Our results can therefore not be explained by constant unobserved and firm idiosyncratic factors, year-specific shocks to innovation or a group of firms in certain industries.

We directly address some economically motivated identifying concerns using matching. We estimate the propensity of a corporation to have at least one angel employee in a logit regression. Size, number of employees, R&D expenses, liquidity, and profitability are positively related to the presence of angel employees at a firm. We match on past patent stock, in order to capture firms with a similar patenting history. We also match on growth opportunities, proxied by Tobin's Q. To the extent that future prospects are incorporated into the stock price, we can reduce concerns that a firm's employees conduct personal investments in order to diversify themselves. In order to make sure we do not capture any life-cycle effects, we also match on firm age. Apart from standard controls, we additionally include squared and cubed terms, as well as simple interactions of our controls in the matching. In a difference-in-differences regression, employing at least one angel investor is related to 5% lower economic value of patents. We exploit the exact timing of the first angel employee at a firm in an event study framework. Importantly, we test for and do not find pre-trends. Our observed effect seems to be confined only *after* the first angel employee at a firm. The effect persists when only looking at angel employees that are present both before and after their investment. This mitigates concerns that angel-specific unobservable characteristics drive the results.

Next, we the concern that unobserved time-varying factors, that do not correlate with observed characteristics, affect whether a firm has angel employees. Therefore, we complement our results with an instrumental variable regression. Recent literature suggests that angel investors and venture capital (VC) can be substitutes (Hellmann and Thiele (2015); Hellmann et al. (2019)). Therefore, we use VC *fund raising* across US states as an instrument that has a negative effect on the number of angel employees, similar in spirit to Nanda and Rhodes-Kropf (2013). We make use of the staggered implementation of the so-called "prudent investor rules" (PIR) across US states following González-Uribe (2020). These rules provide a regulatory change that increases local pension funds' investment in VC. We create our instrument by interacting VC fund raising with the staggered implementation of PIR across US states. The goal of the instrument is to capture regulation-induced competition in the early-stage financing market that is plausibly unrelated to corporate innovation.

We find that our instrument is a strong negative predictor of the number of angel employees and on future innovation. The identifying assumption is that VC fund raising only affects future innovation through angel employees. Previous research has shown that venture capital generates positive spillovers to corporations (Kortum and Lerner

(2000)). This would bias us against finding a negative effect. We validate the exclusion restriction out-of-sample as follows: In order to better capture competition that affects angel investors, we focus on small VC funds, that invest on average less than \$5M. If we, alternatively, aggregate large VC fund raising, we obtain a *positive* effect both on angel employees and future corporate innovation, in line with previous evidence. This strengthens a causal interpretation of the instrumental variable regression.

To take advantage of the detailed employment information, we classify angels whether they have innovation-related roles at their employer. If angel employees indeed have a negative effect on future innovation, we would expect innovation-related angel employees to have a stronger effect on corporate innovation. This is what we find. We also show that the presence of angel employees is not correlated with innovation input, i.e., R&D expenses. Thus, innovation output is reduced while innovation input is unaffected. This makes a change in innovation activity on a firm level an unlikely explanation.We are aware that we do not have a perfect natural experiment to study the effect conclusively. However, we believe that our analyses significantly raise the bar for alternative hypotheses to explain our results.

The question remains: What can explain the observed negative effect of angel employees on corporate innovation? We find that angel employees divert time and effort from their employer to their personal investments. Angel employees might carefully select or actively monitor (treat) their portfolio start-ups. Hence, we hypothesize that a stronger negative effect for ex-post successful start-ups is indicative of an agency conflict. We find this to be the case. Using the total number of failed start-ups as a proxy for treatment or selection intensity, the negative effect is more pronounced if the linked start-ups were ex-post successful.

We now turn the perspective to the point of view of the start-ups and ask the question: Are angel employees beneficial for their start-ups? If indeed angel employees are carefully screening or treating their investments, then we would expect that they have a positive impact on the probability of success of their investments. Indeed, we find that start-ups financed by angel employees have a 6% higher success probability compared to other angel investors. This is an increase of 30% compared to the unconditional start-up success rate and is only slightly lower than the widely studied effect of VC participation. Angel employees are also positively related to measures of innovation quantity and quality of their personal investments. This again is consistent with the view that angel employees divert time and effort from their employer to their start-ups.

In line with agency conflicts of angel employees, we find that the negative relationship is particularly strong for exploratory patents, which are inherently more risky and require more resources. Strict governance can induce career concerns, decrease investment in firm-specific human capital, and can lead managers to focus on short-term routine work. In line with this literature, we find that the negative effect of angel employees on corporate innovation is stronger if the firms face a higher threat of hostile takeover.

Finally, we explore a quasi-exogenous shock which adversely affected the incentives of angel investors: the Small Business and Jobs Act (SBJA), which made angel investments tax exempt after 2010. This shock unexpectedly changed the benefits of angel investing as the expected capital gain of angel investments is increased substantially. This allows to tease out the effect of agency conflicts of angel employees. Indeed, we see that the negative effect is much stronger after 2010. This evidence indicates that recent changes to the *incentives* to invest may lead to detrimental effects on employers.

Our results are robust when we exclude California and Massachusetts based firms. We also extend the analysis on non patent-based measures of innovation and continue to see a negative effect on new product launches, trademarks, and scientific publications. Furthermore, our results also hold when we generalize our results to private rather than public employers.

Our research contributes to the literature in several ways. First, we complement a recent but growing strand which examines the role of angel investors in our economy. Existing literature has so far focused on the role of angel investors in the success of their portfolio companies (e.g. Sudek et al. (2008), Kerr et al. (2014), Lerner et al. (2018)). We complement this literature and examine the previously unexplored role of angel investors in our economy, namely corporate decision making.

Second, we study the importance of human capital for innovation (Custódio et al. (2019), Li and Wang (2021)). Previous literature has studied the effect of managerial traits on corporate innovation (e.g. Faleye et al. (2014), Chemmanur et al. (2019)). We add to this literature that personal investments in start-ups are associated with substantial agency conflicts that negatively affect long-term corporate outcomes such as innovation. Our setting is distinct because we observe a clear personal monetary link with an extreme upside potential. Our analysis is also related to the literature on how off-the-job behavior of corporate executives shape corporate policies (e.g. Cronqvist et al. (2012); Davidson et al. (2015); Falato et al. (2014); Décaire and Sosyura (2021)). We emphasize that we are unable to make a welfare statement. Our findings are nuanced as we highlight a trade-off between the benefits of angel investors for start-ups and the costs for their employer.

The remainder of this paper is structured as follows. Chapter 2 provides a description of how we define and obtain data on angel employees. Chapter 3 provides the baseline empirical results. Chapter 4 explains how agency conflicts likely drive the results. Chapter 5 performs some robustness tests. Chapter 6 concludes.

2. Data

2.1. Angel Investments

Our data of interest are angel investments which are personal equity (or equity-like) investments in early-stage firms. Our research question requires us to know the identity of angel investors. We primarily rely on deanonymized data from Crunchbase. Crunchbase gathers public information initially through crowd sourcing but is now an independent data provider. The vast majority of data is collected through its partnerships with more than 4,000 investment firms, an active community of users, and staff who continuously update data[2].

Angel investments do not need to be disclosed, so we are likely to capture a lower bound of the angel investor universe. A concern is whether the public disclosure of angel

[2] Crunchbase has been compared to traditional datasets and is the most extensive database for early-stage start-up funding round information (Retterath and Braun (2020), Dalle et al. (2017), Ling (2015)). A number of recent papers rely on Crunchbase for data on early-stage private financing rounds such as Kaplan and Lerner (2017), Dimmock et al. (2019), or Edwards and Todtenhaupt (2020).

investments suffers from selection bias. Start-ups might have an incentive to strategically disclose prominent investors as they can serve as a credible signal to the market. Problematic for us would be strategic disclosure by angel employees. If employees of more innovative corporations are less likely to disclose their angel investments, we would then overestimate the negative effect of angel employees. This is unlikely for two reasons. First, we look at the total number of angel employees of the whole corporation, so strategic disclosure needs to be correlated on a firm-year level. Second, in order for this to be a problem, there needs to be a correlation between angel investment disclosure and *future* declining corporate innovation. We do not think that this is likely, however this remains a potential threat to our analysis.

2.2. Employment History

Key to our data collection is to match angel investors to their employer. We manually obtain historical employment data from public LinkedIn profiles. Crunchbase provides individual profile links for the majority of angel investors in our sample. We verify these and collect missing links through manual searches.

The advantage of LinkedIn is that information is standardized and almost all investors provide information on past employer, duration, and their role within the organization. A potential drawback is that our final dataset could be biased towards individuals that are more likely to have an updated LinkedIn profile. For example, well known individuals such as Jeff Bezos might be less likely to have a Linkedin profile page. We mitigate this problem by manually obtaining the employment history of all angel employees with at least 3 investments in our data. We are able to obtain employment histories for 98% of all angel investments. We are therefore confident that a sample bias due to missing employment information is not a major concern.

2.3. Sample Construction

We provide an overview of the sample and the filtering steps in Table 1. More details on data collection and background information is available in Appendix 2. Crunchbase contains information on more than 250,000 funding rounds across 173 countries. We restrict ourselves to angel investments, i.e. we only keep equity or equity-like investments which are tied to individuals. We remove investments tied to venture capital partners and individuals employed in a corporate venture capital unit. We restrict the sample to US early-stage firms in the years 2001 to 2018 due to low data coverage before 2001. With these filters, our data covers a total of more than 70$ Billion early stage financing and includes many well known startups and angel investors. In total, we capture 25,984 investments made by 13,383 unique angel investors across 9,547 unique early-stage start-ups.

Of these investors, we obtain biographies either through LinkedIn or through manual searches. We obtain the full LinkedIn employment history of 9,843 angel investors totaling 88,062 employment observations. We match employer names from LinkedIn to publicly listed firms using a fuzzy name matching algorithm. For this purpose we obtain historical names from CRSP. We standardize names and remove legal suffixes. Then we compute a Levenshtein distance which measures the distance between strings. We manually verify close strings. After matching angel investors to corporations, our final dataset is comprised of 2,100 unique angel employees, 873 unique corporate employers, and 3,328 unique start-ups. This means that 25% of angel investors with observable employment history are at the time of investment employed in a listed corporation. 38% of angel employees are members of the board of directors at their employer. 13% are executives (of which 41% are CEOs) and 51% are classified as others[3]. When we look more closely into the third category, almost all belong to upper management, as most of the angel employees self report their title as: presidents, product managers, and other senior managerial roles, usually in what we would classify as innovation-related functions. Figure 1 visualizes the roles of the angels in our data. According to evidence from business angel surveys, we assume an average angel investment holding period of 5 years[4]. Our sample largely validates survey estimates (The American Angel (2017)). The median (mean)

[3]A small number of individuals have dual roles, e.g. are member of the board of directors and are CEOs.

[4]The American Angel (2017) among others say that the target mean and median duration of a typical angel investment is 5 years. The results are quantitatively and qualitatively similar when assuming that angel employees are keeping their investments for shorter time periods or forever.

funding round in our final data set is \$4M (\$6.4M)[5].

[Insert Figure 1 here]

From the point of view of firms, around 20% of S&P 500 constituents employ at least one angel investor and we capture a significant part of smaller firms as well. Our main variable of interest is the natural logarithm plus one of total number of angel employees at a corporation[6]. Ten angel employees can be mapped to IBM in the year 2016. The company with most angel employees in our sample is Alphabet, to which we can link a total of 202 employees who personally invested across 414 start-ups between 2001 and 2018.

One source of variation in our data comes from the timing of an angel investment. We observe existing employees which first invests in early-stage firms, thus effectively becoming angel investors. A second source of variation is when employees with previous angel investments switch jobs. Effectively, angel investments are tied to the employees and not the employer.

We are likely to capture a lower bound of angel employee activity on a firm level. Angel investments are largely unobserved and we do not claim to be able to create comprehensive data which captures the universe of angel investors. We therefore interpret our variable *angel employee* not as the effect of one single employee, but rather as a proxy for angel investor activity on a firm level. There are significant peer effects associated with investments of coworkers (Ouimet and Tate (2020)). We think that we are thus likely to capture the effect of a more substantial part of the workforce involved in personal investments and not just a few individuals.

[5]Unfortunately we do not observe the individual amount each angel invests, but only the total amount of each financing round. Many rounds include both angel investors and venture capital investors.

[6]This choice is not material to our study. Our results are robust to using the raw number, the log transformed number, and when we alternatively scale the number of angel employees by the total number of directors at a firm. Our results are robust if we define angel employee as a dummy variable set to one if a firm employs at least one angel investor. The results are similar when omitting firms without angel employees.

2.4. Innovation Output

Our main measure of firm innovation is the economic value of patents, measured as stock market reactions to patent grants. We rely on previous work and use patents matched to US firms from Kogan et al. (2017) available from 1926-2019, henceforth KPSS. We are primarily interested to understand whether angel employees provide any private benefit to the shareholders of the firm. As noted in Kline et al. (2019), the KPSS measure is particularly suitable for this purpose as opposed to other measures of innovation. We aggregate our innovation variable on a yearly level and scale by total assets following Kogan et al. (2017). Our second measure of firm innovation is citation-weighted patents. Since younger patents have less time to be cited, we perform a truncation-adjustment and control for year and technology class fixed effects as discussed in Lerner and Seru (2017), and Dass et al. (2017)). We obtain citations until March 8, 2021 directly from the United States Patent Office (USPTO) accessed through Patentsview. Our main regressions only use information until the year 2016, such that each patent has at least 4 years to be cited. In order to identify innovation creation more cleanly, we use the application year of the patent. We use three alternative measures of innovation that are non-patent based: the number of trademarks, new product launches, and science publications. All variables and sources are described in the Appendix. To measure future innovation of the start-up that angel employees invest in, we also match patents to the start-ups in our sample. We perform a fuzzy name matching algorithm and exclude punctuation, capitalization and legal pre- and suffixes. We only keep matched firms if they are located in the same state. We match 306,043 patents to 8,147 start-ups. From this data we compute three variables. A dummy equal to one if at least one patent is granted to a start-up, the log of one plus total citations to all patents of each start-up, and the log of one plus the average number of citations per patent.

2.5. Other Control Variables

We obtain additional control variables from CRSP and Compustat. We largely follow Fang et al. (2014) and control for the following 15 standard control variables: log of market capitalization, research and development expenses, Tobin's Q, profitability, asset tangibility, the log of firm age, the Herfindahl index defined over yearly sales in 4-digit

SIC code, Herfindahl index squared to capture non-linear effects, stock liquidity proxied by the daily mean bid-ask spread, capital expenditures, leverage, financial constraints, past patent stock, and the log of the number of employees. All variables and sources are listed and described in Appendix 1. We winsorize all continuous variables at the 1% level on a firm and year basis. We also control for the presence of a corporate venture capital program following Ma (2020)[7]. For our instrumental variable, we obtain information on the fundraising of venture capital funds from Refinitiv Eikon (formerly Thomson Reuters).

2.6. Descriptive Statistics

Table 2, Panel A presents the descriptive statistics of the variables used in our study. $INNOV_{t+1}$ refers to the innovation output of a firm as measured by the economic value of patents applied in the next year. Our sample statistics are quantitatively similar to previous studies (Fang et al. (2014)). The patent distribution is highly skewed. The mean economic value of patents in our sample is 3% of the book value of a firm. Our main variable of interest, the number of angel employees, is also highly skewed. The vast majority of firms do not have angel employees. We directly address this concern in the upcoming section.

[Insert Table 2 here]

[7] More corporations have active angels than an active corporate venture capital program. There is hardly any overlap between the two ways of investing in startups. It is very rare that an employee invests in a startup and the corporate venture capital program of the employer invests in the same startup. Also, we only see very few interactions between corporations and linked start-ups as measured by cross-citations of patents. We see this as evidence that corporations do not outsource innovation using angel employees. This strengthens our finding that these investments are largely personal and not related to the employer.

3. Empirical Results

3.1. Panel Baseline Regression

To investigate the effect of angel employees on innovation output, we estimate the following panel regression:

$$INNOV_{i,t+k} = \beta \times AngelEmployeeDummy_{i,t} + \gamma \times \mathbf{X}_{i,t} + \theta_i + \phi_{c,t} + \epsilon_{i,t} \tag{1}$$

where i represents firm i and t represents year t. We observe innovation k periods in the future. Since innovation is a long-run process, we measure patent output *INNOV* at the subsequent $k = 1$ to 5 years. *Angel Employee Dummy* denotes the main variable of interest which takes the value of 1 if a firm employs at least one angel employee in a given year and zero otherwise. The vector $\boldsymbol{X}$ represents the 15 standard control variables. The variables θ and ϕ are firm and year fixed-effects, respectively. Year fixed-effects account for yearly-specific shocks to patenting. Firm fixed-effects help us to control for non time-varying unobserved factors on the firm level. We cluster standard errors on a firm level to correct for auto-correlation of innovation at a given firm over time following Fang et al. (2014). The analysis is robust to different fixed-effect structures such as industry-year and different levels of clustering.

[Insert Table A1 here]

The results are presented in Table 3. The estimate of *Angel Employees Dummy* is negative and statistically significant (t-statistics of -3.95 to -4.66) across all specifications. The economic magnitudes implied by the point estimates are also non-trivial. The point estimate in column (1) implies that a firm-year with at least one angel employee is associated with a 3% lower economic value of patents over the next year. The effect is comparable to widely-studied firm characteristics such as R&D expenses.[8] Columns (2) to (5) repeat the analysis with the economic value of patents in the next 2, 3, 4, and 5 years, respectively. The point estimates of *Angel Employees Dummy* continues to be

[8]For example, a one standard deviation increase in R&D expenditure of a firm is related to 0.98% (= 0.14×0.07/100) higher economic value of patents.

negative, which indicates that the negative effect is long-run. The results are similar when we use citation-weighted patents as the dependent variable (see Table A6, t-statistics of -2.71 to -5.24)[9]. This suggests that angel employees are associated with lower economic as well as scientific value of patents.

We perform additional tests for our baseline specification. For ease of interpretation, we define the main variable of interest as a dummy variable. However, we can relax this assumption. Hence, as a first check, we run our baseline model using the natural logarithm plus one of the number of angels as our independent variable. As shown in Table A1, we see that our results remain unchanged. The effect is quantitatively similar when we scale the number of angel employees by the number of top-level managers from BoardEx at a firm-year. The results are also unchanged when limiting the sample to only firms that have angel employees at one point in time (see Table A2).

Next we turn to the dependent variable. Our preferred variable, the economic value of patents, is scaled by assets. We note that the results are similar when using log-transformed citation-weighted patents. The baseline results are robust if we limit the sample to firms that patent, similar to Kogan et al. (2017). The results are shown in Table A3. We additionally perform an inverse hyperbolic sine transformation of our innovation variable[10]. The results are shown in Table A4. We also plot the raw data in Figure A3 and show that a linear relationship looks plausible for our setting. To sum up, zero-inflation is unlikely to explain our results.

We perform a model specification check as suggested by Brodeur et al. (2020). The result is shown in the Appendix in Figure A6. All model specifications lead to similar coefficients. The significance level is robust throughout, which makes model selection an unlikely explanation for our results.

We do not find an effect when we look at R&D expenditures of the firm (see in Table A7 in the Appendix). If patents are an indicator of patent output and R&D an indicator of input, we find evidence for reduced quality of innovation output but no

[9]We additionally perform all future regressions with citation-weighted patents and the results are quantitatively and qualitatively similar. For brevity, we relegate these results to the Appendix.

[10]The inverse hyperbolic sine transformation is defined as $log(y_i+(y_i^2+1)^{1/2})$ and allows to include zeros without adding a constant term.

change of innovation input. To some extent, this rules out concerns that a change in firm strategy can explain our results.

Several explanations prevent us to draw causal inferences. First, our estimates could be prone to reverse causality. If firm innovation is already declining, employees might invest to diversify themselves. Our regression would spuriously correlate a higher number of angel employees with worse innovation even though the reverse is true. To mitigate this, we include a large number of controls that will capture some of these effects. Because of year fixed effects our results cannot be explained by yearly shocks common to all firms. Our results are robust to inclusion of industry-year fixed effects, and can also not be explained by a group of firms in the same industry with angel employees and low future innovation. However, employees might have insider knowledge of decreasing future innovation output and are subsequently more likely to invest in early-stage firms in order to diversify themselves. Next, we directly address identification using two separate strategies.

3.2. Matching

Our first specification to address some alternative hypotheses is propensity score matching (PSM). Our setting is well suited for matching as the universe of listed firms in the US provides us with a large number of control firms as well as readily available control variables. PSM therefore provides a natural environment to tease out treatment effects under the identifying condition that firms are conditionally random except for actual treatment. While angel investments are of course not random on an individual level, the assumption is that by matching on various covariates, they are conditionally random on a firm level.

The covariates contained in the matching help us alleviate some economically motivated alternative hypotheses. We match firms on past patent stock in order to reduce concerns that we capture a mean reversion in innovation. Another explanation is essentially a reverse causality argument: A firm faces low growth opportunities and employees invest in order to diversify themselves. We thus include growth opportunities as proxied by Tobin's Q into the matching. To the extent that future prospects are included in the current stock price, we incorporate this information in our matching. We also explicitly match on firm age to account for possible life-cycle effects. One of the main advantage of PSM is that it mitigates functional form misspecification. Therefore, on top of the standard control variables, we include second and third order polynomials as well as simple interactions between all control variables. The specification presented in equation 2 includes 115 variables in total that can potentially predict the number of angel employees. We thus compare firms with similar observable characteristics in a number of dimensions that only differ on the existence of angel employees.

We use PSM to estimate the propensity of firms to be treated following Rosenbaum and Rubin (1983). The treatment variable in our case is set to one if a corporation employs an active angel investor in a given year and zero otherwise. We calculate the predicted propensity to be treated in the following logit regression:

$$AngelEmployeeDummy_{i,t} = \alpha + \beta \times \mathbf{X}_{i,t} + \epsilon_{i,t} \tag{2}$$

Based on these predicted propensities we perform matching as follows. A treatment firm is chosen one year before treatment. The matching algorithm chooses the three closest counterfactuals (with replacement) to a firm with angel employees. In Table 4, we see that control and treated firms are virtually indistinguishable across a large number of characteristics. For a visual representation of all variables used in the matching algorithm, we refer to Figure A4. Size, number of employees, research and development expenses, liquidity, and profitability positively predict the number of angel employees on a firm level. Tangibility, capital expenditures, and leverage negatively predict the number of angel employees. Overall, matching significantly reduces covariate imbalance and no variable is significantly different in the matched sample.

[Insert Table 4 here]

After matching, we run a difference-in-differences regression following Bertrand et al. (2004). We exploit the precise timing of angel investment on a firm level in the following regression:

$$INNOV_{i,c} = \phi \sum_{c=-4}^{c=+3} D_c \times \sum_{c=-4}^{c=+3} \beta_c D_c \times Treat_i + \gamma \times \mathbf{X}_{i,c} + \theta_t + \phi_i + \epsilon_{i,c} \tag{3}$$

Treat takes the value of one for firms with angel employees and zero otherwise. We interact the treatment dummy with event time dummies starting 4 years before treatment and 4 years after treatment (starting in year 0). We include firm and year fixed effects as well as all simple controls in the regression. Standard errors are clustered on the firm level.

Table 5 presents the results of our matched sample regression analytically. The presence of angel investor(s) decreases future economic value of innovation by approximately 5% relative to the mean. Columns (1)-(2) show the effect on economic value of patents and columns (3)-(4) on citation-weighted patents. The pre-trends are not significantly different from 0, with the exception of one coefficient. The single statistically significant coefficient is also positive. We therefore do not see evidence for pre-treatment trends of firms that employ angels. The negative effect is prominent only after the first angel investor is employed at the firm.

[Insert Table 5 here]

Angel employees might fundamentally differ on other important characteristics. They could differ in their skills, or risk appetite. We show that the negative effect of angel employees seems to be confined to the time after angel investment. In order to directly address that any unobserved employee specific characteristic drives our results, we only consider the sub-group of angel employees that are present in a single firm both before and after their investments. Then, we re-run our propensity score matching regression. Thus, we keep the angel characteristics fixed for the same firm. We continue to find that angel employees have a negative effect on firm innovation *only* after their angel investments.

Our matching results are not sensitive to model specification. In Figure A5, we perform a robustness test similar to DeFond et al. (2017). In 3,000 trials, we randomly vary the number of nearest neighbors between 1 and 3, and on top of our basic controls a random number of control variables. We see that the effect is negative for all 3000 trials and we receive a significantly negative effect in more than 88% of all cases. This makes it unlikely that the negative effect is by chance or that we picked a specific model that delivers good results. Lastly, in untabulated results, the results are similar when we match according to categorical variables such as industry or state.

3.3. Instrumental Variable Regression

To ideally infer a causal relationship we would need to randomize angel investments across US firms. As this experiment is not feasible, we use an instrumental variable approach. Recent literature has shown, theoretically (Hellmann and Thiele (2015)) and empirically (Hellmann et al. (2019)), that venture capital and angel financing can be substitutes. We use small VC fund raising across US states interacted with the staggered implementation of so-called "prudent investor rules" (PIR) across US states following González-Uribe (2020), as an instrument for the number of angel employees. To construct the instrument, we interact the PIR with aggregate total small VC fund raising by year and state in the preceding year. To make sure that VC funds can act as a plausible substitute for our sample of angel employees, we require the funds to invest less than \$5M on average per company in their portfolio (small VCs). We take this cut-off based on the average funding round size (of \$6.4 million) that our sample angel employees invest in. We measure the average sum invested of each VC fund and divide the total amount of money invested by the total number of companies that they invested in. This instrument is novel for angel investments but similar ones have been used in the VC literature (Gompers and Lerner (2000), Nanda and Rhodes-Kropf (2013).

The goal of the instrumental variable regression is to capture variation in the number of angel employees due to competition in the private equity market and is unrelated to corporate innovation. The identifying assumption is that our instrument does not directly affect future innovation of the employers of angel investors. We argue that this assumption is plausible for the following reasons: 1) Private equity funds are committed before investment and do not necessarily imply actual investments. Since we take *fund raising* in the preceding year and not investments, we do not capture contemporaneous supply effects on the market. 2) A large part of funds in the private equity market comes from university endowments and pension funds (Nanda and Rhodes-Kropf (2013)). Such investors are often constrained to invest locally (Cumming and Dai (2010); González-Uribe (2020)). This variation in fund raising is more likely to be exogenous to corporate innovation. 3) Our identification strategy additionally relies on the staggered implementation of the PIR across states. The PIR allows state pension funds that were not covered in the Employee Retirement Income Security Act of 1979 to invest in venture capital. We thus have time-varying regulatory changes that lead to more venture capital investments. Furthermore, investments of pension funds tend to be local either due to a local bias effect (Cumming and Dai (2010)) or legal restrictions of pension funds to promote local development (see González-Uribe (2020) and the literature therein). The consequence of fewer angel employees is likely not an intended consequence and the regulation itself is unlikely to be driven by corporate innovation related reasons at a state level. 4) Hirukawa and Ueda (2011) show that VC has no effect on innovation, whereas Kortum and Lerner (2000) show that VC investments create significant positive spillovers. More recently, Howell et al. (2020) show that VC investments tend to be pro-cyclical rather than counter-cyclical. Such evidence biases us against finding a negative effect of our instrument on corporate innovation.

Our hypothesized mechanism is that the small VC fundraising complemented by the regulatory change introduced by the PIR across US states quasi-exogenously crowds out angel investors. We use the fact that angel investments also tend to be local and proxy exposure of corporations by their headquarter location. Due to the difference-in-differences nature of the methodology, states that did not enact the PIR cannot drive the effect. Panel A of Table 6 presents the results of the first stage regression. Consistent with the crowding-out hypothesis, small VC fund raising interacted with the PIR strongly negatively predicts angel employees. The F-statistic is between 16 and 43 across specifications.

[Insert Table 6 here]

Turning to the second stage in Panel B, the point estimates are statistically significant across all specifications. The point estimate in Column (1) imply that a one standard-deviation increase in the average predicted likelihood to have an angel employee is associated with a 4.6%(= 0.02×2.3) lower economic value of patents in the next year[11]. The point estimates are larger compared to the OLS specification. However, the point estimates converge to the OLS estimates, the higher the F statistic. As documented in Table A8 in the Appendix, we reach similar results when using citation-weighted patents.

We note that the coefficient of the instrumental variable regression in the second stage and the propensity-score based matching estimate is higher than the coefficients from the OLS panel regression. Additionally, we also note that the economic magnitude implied by them is marginally higher compared to the OLS regression. There are two possible reasons for this. As discussed before, angel investment activity is primarily unobserved and hence measured with errors. Therefore, we are likely to capture a lower bound for angel employee activity. The instrumental variable regression may pick up unobserved angel investment activity and account for the measurement error. It is likely that a firm already has many more angel employees whereas we only assign few individuals to this particular firm. Using VC fund raising, we are adjusting for these unobserved angel employees. We also note that, assuming unbiasedness, the OLS regression estimates an average treatment effect, whereas the IV estimates a *local* average treatment effect. For our setting, it is plausible that the subset of employees that can be dis-incentivized to invest in early-stage firms (compliers) are the ones that are likely to have a higher negative impact. In the next chapter, we will present evidence which suggests that agency conflicts are the reason for the observed negative effect. The subset of employees that are likely to invest regardless of competition in the early-stage financing market (never-takers) might be inherently less prone to this agency conflict. This would imply a stronger localized effect.

Finally, we present additional evidence supportive of the validity of our instrument. We test the validity of the exclusion restriction out-of-sample as follows. Our instrument only relies on small VC funds that are more likely to compete with angel investors. Alternatively, if we aggregate large VC fund raising, we can directly test the effect of large VC fund raising on angels or future innovation. By and large, we do not see a

[11]The standard deviation of the predicted values of the likelihood of having an angel employee as estimated from the first stage is 0.02

negative effect on angel employees or corporate innovation, but rather a positive one. We show this regression in Table A9. Large VC fund raising has a positive effect on future innovation and significantly so for up to two years into the future. This result is consistent with Kortum and Lerner (2000) and Howell et al. (2020). The effect on the number of angel employees is also positive and significant. An alternate hypothesis would, therefore, need to explain how the exclusion restriction can be violated only for small VC funds and not for large VC which due to their size should if anything have a stronger (and negative) impact on corporations.

One confounding effect would be if VC fund raising leads to more competition for resources such as human capital. Our instrument would pick up this negative effect of VC fund raising on innovation as additional funds help startups to poach employees from corporations. Thus, we directly test whether VC fund raising is correlated with executives exiting their corporate jobs. In unreported results, we find that, if anything, VC fund raising is negatively associated with exit of firms' executives.

In the absence of a natural experiment, we are unable to rule out all alternative hypotheses what factors could affect our observed relationship. However, the results of our baseline, matching, and instrumental variable regressions significantly raise the bar for alternative hypotheses to explain our findings.

3.4. The Effect of Innovation-related Angels

To take advantage of the detailed profile information obtained from LinkedIn, we split the total number of angel employees into those that are likely to work in innovation-related functions and those that are not. Based on the textual title information of each employee, we tag employees with the words: "product", "innov", "research", among other keywords as innovation-related and angel employees with titles such as "finance" or "legal" into non-innovation related angels. We then run the baseline regression with the key independent variable split into two parts: innovation-related and non-related angel employees. Panel A of Table 7 shows a stronger negative effect for the sub-sample of angels that are classified as innovation related angels. Hence, the negative effect of the agency conflict on innovation is pronounced if the angel employees are likely to be directly related to corporate innovation.

[Insert Table 7 here]

Next, we split the sample into CEO and board members in one group and all others into a second group. As mentioned earlier, 13% of the sample are classified as executives, 38% are members of the board of directors and 51% are classified as others, predominantly upper- and middle-level management[12]. Given the large literature which examines the role of CEOs and boards on corporate policies, one can expect that the negative relationship to corporate innovation is more severe when such high-level management is faced with the agency conflict. However, as reported in Panel B of Table 7, we do not observe a large difference between the two groups. Our results show that these individuals are also important to consider for innovation-related outcomes in line with evidence presented in Hellmann and Thiele (2011).

4. Agency conflicts

In the following, we explore possible channels. We present a string of evidence which suggests agency conflicts drive the negative relationship between angel employees and future firm innovation. Attention is a limited resource and agents strategically allocate time to their tasks. Essentially, an angel employee faces the conflict to exert effort at her corporate employer and her personal investment.

4.1. Ex-Post Successful Start-ups

Angel investments are characterized by high risk and potentially high reward. Angel investors often receive so-called *homerun* returns of more than 100% of their initial investment (Wiltbank et al. (2009)). Such a risky endeavor might incentivize angel employees to spend significant time to select or monitor their own investments rather than exert effort at their corporate employer. In the following we hypothesize that investments that are relatively successful, i.e., which have not failed yet, should lead to a stronger agency conflict. This can be for a number of reasons. The investment duration is likely longer compared to a start-up that fails. For ongoing investments, angels might be engaged

[12]There is a small number of angels with dual roles, e.g. they are both CEO and director.

with their start-ups in numerous ways to help them succeed. Additionally, if some angels obtain board seats, there will be time intensive board meetings for follow-on financing rounds, or if the start-up ultimately is acquired, or goes public. Finally, for relatively more successful start-ups (observed ex-post), angel employees might be particularly engaged and select such investment opportunities. Overall, we expect that the negative relationship to be stronger for firms associated with relatively more successful (or non-failed) start-ups.

To test this, we incorporate ex-post information in our analysis. We mark start-ups as failed if they are flagged as defunct or did not receive additional funding in the last 5 years. We take the number of failed and non-failed start-ups of all employees' investment for each corporation. We then run the baseline specification of equation 1. We replace the *Number of Angel Employees* variable with *Non-Failed Start-ups* and *Failed Start-ups* which is the natural logarithm of the number of non-failed and failed start-ups per firm per year, respectively.

[Insert Table 8 here]

Table 8 document our results. Links to non-failed start-ups through existing angel employees are associated with lower future firm innovation. The effect for non-failed start-ups is economically higher and more significant even though the number of non-failed start-ups in the sample is considerably lower. The coefficient for failed start-ups is however still negative, but not nearly as significant. These coefficients are also statistically different from each other from year three onwards at the 5% level.

4.2. Do Start-ups benefit from Angel Employees?

To explore this further, we now turn to the start-up perspective. If angel employees indeed divert time and effort from their employer to their investments, then we expect to see a significantly higher probability of success of start-ups financed by angel employees compared to other angel investors. This can again be because angel employees are skilled at selecting their investments or because they are better at advising them.

We test this hypothesis in Table 9. We regress the presence of an angel employee on the probability of start-up success. Our sample is composed of the universe of all angel financed start-ups. Thus, we compare whether start-ups financed by angel employees are more successful compared to other angel investors. We measure start-up success with a dummy variable equal to one if the start-up was ultimately acquired (M&A) or went public (IPO). We also look at future innovation of the start-ups as follows: We set a dummy equal to one if a start-up owns a patent. Additionally we compute two measures of the quality of start-up innovation. The log of one plus the total citations to all patents of each start-up and the log of one plus the average number of citations per patent. Additionally, we control for start-up age, whether a VC invested in an early funding round, and the total amount of financing across funding rounds. We include $City \times Year$ fixed-effects following Dimmock et al. (2019) to account for any unobserved shocks which impact start-up success at the city-year level.

[Insert Table 9 here]

Compared to the universe of angel-backed start-ups, the presence of angel employees increases the likelihood of an successful exit by 6% on average. Compared to the unconditional start-up success rate of 20%, this is an increase of 30% and is only little lower than the effect of the widely studied effect of VC participation. Angel employees also have a significant positive impact on future innovation of their start-up. Start-ups financed by angel employees are more likely to patent and their patents are cited more frequently. We see a positive effect on how many total citations a start-up receives and on citations per patent.

Overall, we present both sides of the medal. On the one hand, angel employees are detrimental for the corporate employer. On the other hand, start-ups seem to benefit from angel employees' participation. These results are consistent with the hypothesis that angel employees seem to divert time and effort from their corporate employer to their personal investments.

4.3. Incentives to Invest: Evidence from a Natural Experiment

In order to identify the effect driven by angel employees' *incentive* to engage with their portfolio start-ups, we exploit the passage of The Small Business and Jobs Act 2010

(SBJA). The regulatory change presents a plausibly exogenous shock to the angel employees' incentive to be more involved with their invested start-ups. The SBJA allows investors to exclude 100% of the eligible gain from qualified small business stock (QSBS) upon sale or exchange from September 27, 2010 onwards (Edwards and Todtenhaupt (2020)). To qualify as a QSBS, the firm must be listed as a domestic C-corporation and have less than $50M in total assets. Exemption from capital gains taxes are granted if an angel investor holds her investment for at least 5 years. Some industries are excluded, however, the majority of start-ups in our sample are in treated industries[13].

This regulatory change provides us with a unique setting to test some predictions using our data. In principal, if angel investments are tax exempt, this should 1) incentivize employees to become angel investors and 2) conditional on being an angel investor, there are more incentives to divert time and effort as future capital gains are tax exempt. We are unable to use 1) as individuals self-select to become angel investors. However using 2) we argue that if agency conflicts indeed drive the observed negative effect, tax exemption of angel investments should lead to a stronger negative effect. We note that our objective is not to exogenize angel employees across firms, rather, we attempt to disentangle the *incentive* of angel employees to engage with their portfolio firms on the economic value of patents.

$$INNOV_{i,t+k} = \alpha + \beta_1 \times Treated_{i,t} + \beta_2 \times Treated_{i,t} \times After_t + \gamma \times \mathbf{X}_{i,t} + \epsilon_{i,t} \quad (4)$$

In order to test our hypothesis, we run a difference-in-difference regression (as shown in Equation 4), where we define $After$ as a dummy equal to one in the years after 2010. *Treated* is a dummy variable equal to one if there is at least one angel employee who invested in QSBS eligible start-ups during our sample period for a particular firm in a given year. We identify start-ups qualified for the capital gains tax exemption following Edwards and Todtenhaupt (2020). The coefficient of interest is β_2 on the interaction term $Treated\times$. If agency conflicts through incentives to engage with their portfolio start-ups

[13]Explicitly excluded are for example: financial services, accounting, law, farming, hotels, among others.

are driving the negative effect between angel employees and the future economic value of patents, then we would expect the coefficient β_2 to be negative. This is indeed what we find. In Table 10, the interaction coefficient is always negative and becomes statistically and economically significant from year two onwards. In terms of economic magnitude, we see that treated firms have 2.9% lower economic value of patents in the third year and 5% in the fifth year. This evidence indicates that recent changes to the *incentives* to invest lead to detrimental effects on employers' innovation quality.

[Insert Table 10 here]

4.4. Exploratory vs. Exploitative Patents

We also look at what type of innovation declines. For this purpose, we differentiate between exploratory and exploitative patents following Brav et al. (2018) and Custódio et al. (2019). A patent is considered exploratory (exploitative) if more than 80% of its citations are based on new knowledge (existing knowledge). Existing knowledge is defined as all patents invented by the firm and all patents cited by the firm's patents filed over the past five years. We re-run our analysis in Table A1 and replace the dependent variable with the average economic value of the exploratory and exploitative patents. Even though exploratory innovative activities may alter the future technological landscape, they are inherently more uncertain and are more likely to fail in early stages compared to exploitative projects (March (1991)). To pursue exploratory innovation strategies requires managers to spend more time and effort in the firm and take on more risks. We therefore hypothesize that exploratory patents should be more affected by such an agency conflict.

[Insert Table 11 here]

The results of the analysis is presented in Table 11. Row 1 of the table shows that the angel employees are significantly negatively related to the economic value of exploratory patents. We do not see similar pattern for exploitative patents in row 2 of the table. This is consistent with the hypothesis that agency conflicts associated with angel employees drive our results.

4.5. Evidence from Hostile Takeover Threat

In this section we explore whether governance mechanisms moderate the relationship between angel employees and future firm innovation. There is a large literature that studies the role of governance on innovation. One strand of the literature predicts that strong governance disciplines managers by keeping them engaged in value-enhancing projects within the firm. When it comes to innovation, the literature predicts that strong governance has an adverse effect on firm output. Strong governance might disincentivize incumbent managers to exert effort and develop firm-specific human capital. For example, Holmstrom (1989), Manso (2011), Atanassov (2013), Bernstein (2015) show theoretically and empirically that lower entrenchment and job security might not be optimal for pursuing innovative projects. This might skew incentives for the managers to focus on routine work, pursue sub-optimally risky projects in the long-run and invest less human capital in their employer. In this case, strong governance might further exacerbate the negative impact of angel employees on firm innovation.

We test these predictions using a measure of the threat of hostile takeover. Cain et al. (2017) develop an index of takeover susceptibility by taking into account legal determinants, macro-economic factors, and firm characteristics. We categorize firms as having a high threat of hostile takeover if their average hostile takeover threat index is greater than the median value for all the firms in the cross-section. Subsequently, we rerun our baseline specification in equation 1. We interact the number of angel employees with a dummy equal to one if a firm has a hostile takeover threat greater than the median.

[Insert Table 12 here]

In Table 12, the negative effects of angel employees on firm innovation is significantly higher for firms having a greater threat of hostile takeover. Across all specifications, the point estimates for firms located in states with higher hostile takeover threat are at least as large as the main effect of having at least one angel employee. These results are in line with the strand of literature which advocates higher entrenchment in order to motivate managers to spend effort on firm innovation. Manso (2011) emphasize the importance of entrenchment for motivating innovation. Atanassov (2013) document that hostile takeover threat negatively impacts firm innovation. In a similar vein, Bernstein (2015) documents the declining innovation quality in firms having non-entrenched CEOs after their IPOs. In a more recent study, Baran et al. (2019) documents the role of entrenchment induced by dual-class share structure on innovation. Our results complement this strand of literature and show that agency conflicts induced by angel employees can be mitigated if managers are provided more control and if career concerns are alleviated.

5. Robustness

5.1. Non-Patent-Based Measures of Innovation

We address possible concerns on the use of patents as a measure for firm innovation. After successful innovation, a corporation faces the challenge to either patent or keep the invention secret (trade secret). Since our dependent variable only captures disclosed patents, if the most valuable inventions are not disclosed and protected due to low imitation costs, then this would lead to measurement error in our estimates. It can also be the case that firms do not file patents, but are still innovative Koh et al. (2021). Therefore, we obtain data on three non-patent based outcome variables: trademarks, new product launches, and scientific publications. Firms have high incentives to file trademarks and launch new products. Compared to patents, there is less substitution with trade secrets.

[Insert Table 13 here]

If innovation output is reduced, then one would expect to find fewer trademarks, new product launches, and scientific publications. Indeed, that is what we find. Angel employees are associated with fewer new product launches over the subsequent 1 to 5 years in Panel A of Table 13. The point estimates suggest that a firm-year with at least one angel employee is associated with approximately 10% fewer product launches after three years ($= exp^{-0.11}$). Similar conclusions can be drawn from trademarks in Panel B, and scientific publications in Panel C of Table 13.

5.2. California and Massachusetts Firms

We also investigate whether our results are driven by some sub-sample of firms. One major concern is that our results are sensitive to the exclusion of California (CA) and

Massachusetts (MA). For example, Lerner and Seru (2017) provide evidence that innovation in CA and MA are higher compared to other states and failure to account for differences might bias our findings. Hence, we re-run our baseline specification and exclude firms headquartered in CA or MA.

[Insert Table 14 here]

We see in Table 14 that the results hold when we exclude firms based in CA or MA. In Panel B the results are also robust when only considering CA or MA based firms.

5.3. Private Firms

Our analysis so far has focused on the effect of angel employees on publicly listed corporations. In this section we test whether the negative relationship holds when we consider private firms. For this purpose, we rely on data from ORBIS. We limit our analysis to firms with at least 10M$ of turnover in the last reporting year. We perform a name matching algorithm in order to match patent data from the USPTO as well as angel employment data to the remaining sample of firms.

[Insert Table 15 here]

The results are shown in Table 15. We observe that the effect on angel employees is negative from and statistically significant after year 2. By and large, the results are comparable to the results when we only consider publicly listed firms. Our observed negative effect is thus generalizable to private firms.

5.4. Competition for Human Capital

It is possible that investments in start-ups provide angel employees with signals about their own entrepreneurial ability. They subsequently might leave their corporate employment to become founder themselves (Babina (2020)). In this way, firms would lose some of its crucial human capital input for high quality innovation and as a consequence, the innovation of the firm declines. If such a mechanism is at play, then human capital loss rather than agency conflict might be behind our results.

We test this possibility and examine the likelihood of angel employees to become founders. To conduct this analysis, we match the entire sample of founders available in Crunchbase to BoardEx executives. In this way, we match almost 32,000 unique executives to the Crunchbase founders who founded a start-up after 2001. Of these, 304 executives belong to our sample of angel employees. We see that very few angel employees found a start-up. In Table A11, we show the results more systematically after we control for various executive level characteristics. We find a negative and statistically significant coefficient for angel employees. This suggests that angel employees in our sample are less likely to become a founder compared to other executives covered in BoardEx. Our results are thus unlikely to be due to a "brain drain": angel employees which leave their employers to found start-ups.

6. Conclusion

Angel investors negatively impact innovation of their corporate employer. We find the result to be consistent across various measures of innovation, namely, economic value of patents, citation-weighted patents, new product launches, trademarks, and sciency publications. The negative relation is driven by innovation-related employees, and those that invested in successful start-ups. However, we also find that such angel employees seem to have a positive impact on start-up success. The results are primarily valid for exploratory patents and firms with high hostile takeover threat. Finally, we show that policy instruments such as the SBJA of 2010 skewed incentives of angel employees to manage their personal investments. This, in turn, has an adverse effect on innovation quality of their corporate employers. Taken together, our analysis suggests that agency conflicts are a driver of the negative relationship between angel employees and future firm innovation. Employees divert time and effort from their employers to their personal start-up investments.

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Table 1 – Sample Selection Steps

This Table shows the filters applied and details on how the sample was selected. The third column gives the corresponding number of observations left in each step.

No.	Sample Selection	No. of Observations
(1)	All Investments tied to individuals (persons) in Crunchbase at the point of data collection (March 2019)	51,209
(2)	Only investments between 2000-2018	49,711
(3)	Remove the following investment types: Product Crowdfunding, Grants, ICOs, Non-equity Assistance, post-IPO Funding, Secondary Market, Debt Financing, Corporate Rounds	48,951
(4)	Only investments into start-ups headquartered in the US	30,610
(5)	Only investments by angels employed at publicly listed corporations (25% of all angels)	7,885
(6)	Angel investors are employed at a publicly listed corporation at time of investment	3,739

Figure 1 – Role of Angel Employees

This Figure visualizes the roles of angel employees in our data. Roles are defined as the position the angel employees list in their LinkedIn profile. The size of the font is weighted by counts, i.e. more frequently mentioned roles are displayed more prominently.

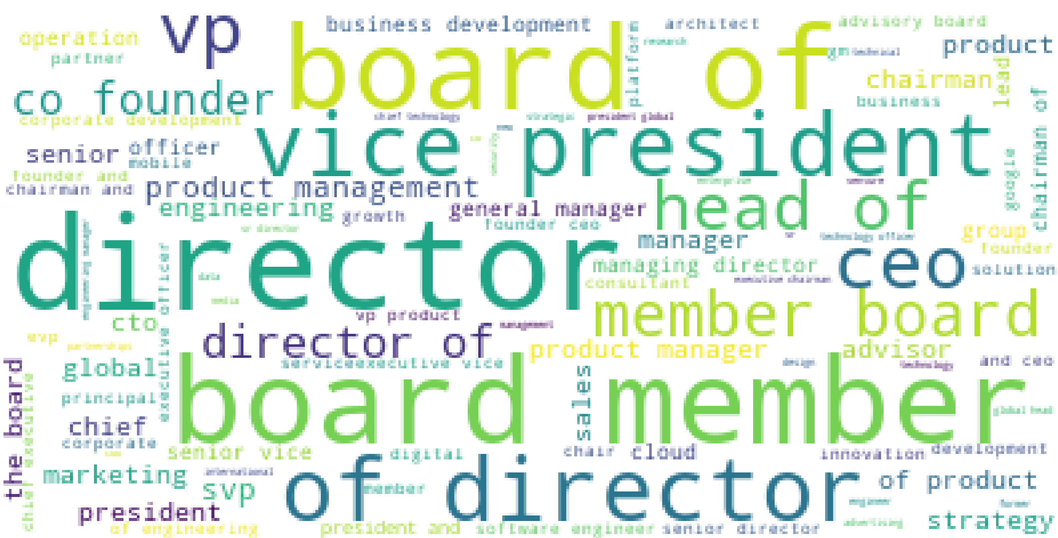


Table 2 – Summary Statistics and Industries with Angel Employees
Panel A shows the summary statistics of the sample. Variable definitions are provided in the Appendix. Panel B shows the top and bottom six SIC industries that employ the most and the least angel investors. For each industry we list two example firms.

Panel A: Summary Statistics

Variable	N	Mean	SD	Min	25%	Median	75%	Max
$INNOV_{t+1}$	55428	0.03	0.09	0.00	0.00	0.00	0.01	0.86
Number of Angel Employees	61578	0.02	0.17	0.00	0.00	0.00	0.00	4.37
Angel Employee Dummy	61578	0.03	0.16	0.00	0.00	0.00	0.00	1.00
Size	61578	6.62	2.16	1.63	5.02	6.55	8.10	12.20
R&D Expenditures	61578	0.06	0.14	0.00	0.00	0.00	0.07	1.19
Tobin's Q	61578	2.02	1.60	0.42	1.09	1.49	2.30	12.36
Profitability	61578	0.03	0.27	-2.01	0.01	0.10	0.15	0.43
Tangibility	61578	0.27	0.25	0.00	0.07	0.18	0.42	0.93
Firm Age	61578	2.35	1.02	0.00	1.79	2.48	3.09	4.20
Herfindahl-Index	61578	0.26	0.20	0.00	0.12	0.19	0.32	1.00
Herfindahl-Index Squared	61578	0.11	0.18	0.00	0.01	0.04	0.11	1.00
Liquidity	61578	0.01	0.02	0.00	0.00	0.00	0.01	0.20
Capital Expenditures	61578	0.05	0.06	0.00	0.01	0.03	0.06	0.43
Leverage	61578	0.22	0.22	0.00	0.01	0.17	0.34	1.25
Financial Constraints	61578	0.65	0.48	0.00	0.00	1.00	1.00	1.00
Patent Stock	61578	0.08	0.27	0.00	0.00	0.00	0.02	3.33
Number of Employees	61578	1.26	1.30	0.00	0.20	0.79	1.97	7.74
Corporate Venture Capital	61578	0.02	0.13	0.00	0.00	0.00	0.00	1.00

Panel B: Industries with Angel Investor Employees

	Most Angel Investors		
Rank	SIC	Description	Example firms
1	7370	Services-Computer Programming, Etc.	Alphabet, Facebook
2	7372	Services-Prepackaged Software	Microsoft, Adobe
3	5961	Retail-Catalog & Mail-Order Houses	Amazon, Wayfair
4	2836	Biological Products	Moderna, Unity Biotech
5	7374	Services-Computer Processing, Data Preparation	Square, Paypal Holdings
6	3663	Radio & TV Broadcasting & Comm. Equipment	Apple, Nokia
	Least Angel Investors		
Rank	SIC	Description	Example firms
1	7011	Hotels & Motels	Marriott Intl, Wyndham Hotels
2	2911	Petroleum Refining	Exxon Mobil, Chevron
3	2860	Industrial Organic Chemicals	Celanese, Westlake Chemical Partners
4	1311	Crude Petroleum & Natural Gas	Conocophillips, Pioneer Natural Resources
5	4911	Electric Services	American Electric Power, Dominion Energy
6	3714	Motor Vehicle Parts & Accessories	Gentex, Garrett Motion

Table 3 – Baseline Regression: Angel Employees and Economic Value of Patents
This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents scaled by assets (Kogan et al. (2017)) over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. The variable of interest $AngelEmployeeDummy$ is equal to one if a firm has at least one angel employee in the year. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Angel Employee Dummy	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(-4.25)	(-4.36)	(-4.66)	(-4.09)	(-3.95)
Market Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-7.08)	(-7.78)	(-7.84)	(-6.17)	(-6.04)
R&D Expenditures	0.08***	0.05***	0.03**	0.01	-0.03**
	(5.89)	(4.18)	(2.36)	(0.80)	(-2.01)
Tobin's Q	0.00***	0.00***	0.00*	-0.00	0.00
	(5.94)	(3.86)	(1.95)	(-0.06)	(0.34)
Profitability	0.00	0.00	0.00	-0.00	-0.01
	(0.38)	(1.03)	(0.68)	(-0.98)	(-1.61)
Tangibility	-0.00	-0.01	-0.01	-0.01	-0.01*
	(-0.06)	(-1.12)	(-1.27)	(-1.43)	(-1.92)
Age	0.00	0.00	0.00	0.00	0.00
	(1.04)	(1.50)	(1.10)	(0.53)	(0.34)
Herfindahl-Index	0.03	0.03	0.02	0.03	0.04*
	(1.46)	(1.35)	(1.19)	(1.46)	(1.68)
Herfindahl-Index Squared	-0.01	-0.01	-0.01	-0.02	-0.03
	(-0.73)	(-0.54)	(-0.60)	(-1.15)	(-1.55)
Liquidity	-0.14***	-0.18***	-0.21***	-0.21***	-0.13***
	(-4.85)	(-6.77)	(-8.18)	(-7.91)	(-4.70)
Capital Expenditures	0.01	-0.00	-0.01	0.01	0.02**
	(1.09)	(-0.09)	(-0.83)	(1.15)	(2.08)
Leverage	0.00	0.00	0.00	0.00	0.00
	(0.15)	(0.45)	(0.55)	(0.75)	(0.42)
Financial Constraints	-0.00*	-0.00**	-0.00**	-0.00	-0.00
	(-1.83)	(-2.00)	(-1.99)	(-1.28)	(-0.54)
Patent Stock	-0.02***	-0.02***	-0.03***	-0.03***	-0.03***
	(-3.71)	(-3.49)	(-4.47)	(-3.79)	(-4.23)
Number of Employees	-0.01***	-0.01***	-0.01***	-0.01***	-0.01**
	(-3.79)	(-3.96)	(-3.51)	(-3.05)	(-2.54)
Corporate Venture Capital	0.02	0.01	0.01	0.02	0.02
	(1.27)	(0.83)	(0.79)	(1.24)	(1.42)
Observations	54,514	49,162	42,341	36,412	31,332
R-squared	0.67	0.67	0.69	0.70	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

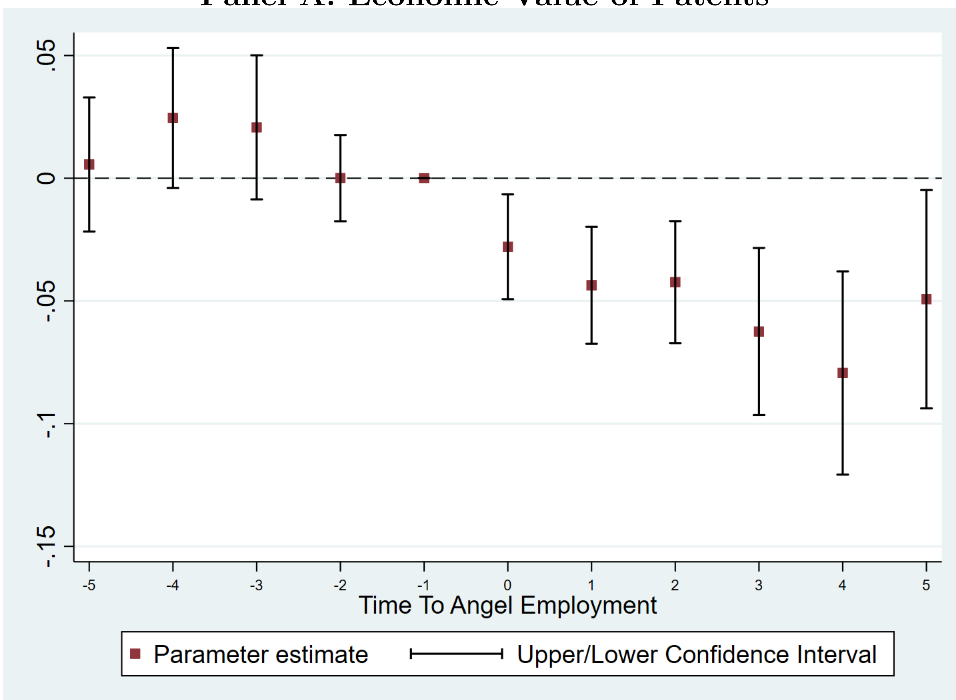
Table 4 – Matching Statistics: Covariate Means
This figure presents covariate distributions before and after matching. We show the mean of our control variables in the treatment and control group. Treatment is defined as a firm which employs at least one angel employee. We split according to the mean before (Pre-Match) and after (Post-Match) matching. We note that for brevity we only show a subset of the variables used for propensity score matching. On top of the variables shown here, we include polynomials of second and third order as well as simple interactions between all control variables. The statistics look qualitatively and quantitatively similar when including all variables. We provide a visual representation of the matching for all variables in the Appendix. Variable definitions are provided in the Appendix.

	Pre-Match		Post-Match		Differences t-test	
Variable	Treat-ment	Control	Treat-ment	Control	Pre-Match	Post-Match
Size	8.08	6.57	7.92	8.03	11.89	-0.59
R&D Expenses	0.08	0.07	0.08	0.09	0.78	-0.49
Tobin's Q	2.48	2.58	2.43	2.35	-0.03	0.59
Profitability	0.05	0.00	0.05	0.04	1.13	0.40
Tangibility	0.16	0.28	0.16	0.17	-7.90	-0.84
Age	2.46	2.47	2.43	2.49	-0.11	-0.61
Herfindahl-Index	0.29	0.26	0.25	0.27	-0.08	-0.93
Liquidity	0.00	0.01	0.00	0.00	-6.93	0.50
Capital Expenditures	0.04	0.05	0.04	0.04	-3.29	-.022
Leverage	0.20	0.23	0.20	0.22	-1.73	-1.71
Patent Stock	0.08	0.11	0.07	0.08	-0.90	-0.64
Number of Employees	1.89	1.23	1.77	1.82	8.80	-0.42
Financial Constraints	0.59	0.66	0.58	0.64	-2.44	-1.55

Figure 2 – Propensity Score Matched Regression: Effect of Angel Employees on Corporate Innovation

This figure shows the results of the difference-in-difference equation 3. The figure plots the average treatment effect on the treated from year $t-5$ to $t+5$. $t = 0$ is the first year of employment of the angel employee in a treated firm. The point estimates have been estimated using year $t = -1$ as the baseline year. The y-axis presents the measure of innovation output. For Panel A, it is the economic value of patents following Kogan et al. (2017). For Panel B, it is the truncation-adjusted citation-weighted value of patents. Confidence intervals are at the top/bottom 5%.

Panel A: Economic Value of Patents



Panel B: Citation-Weighted Patents

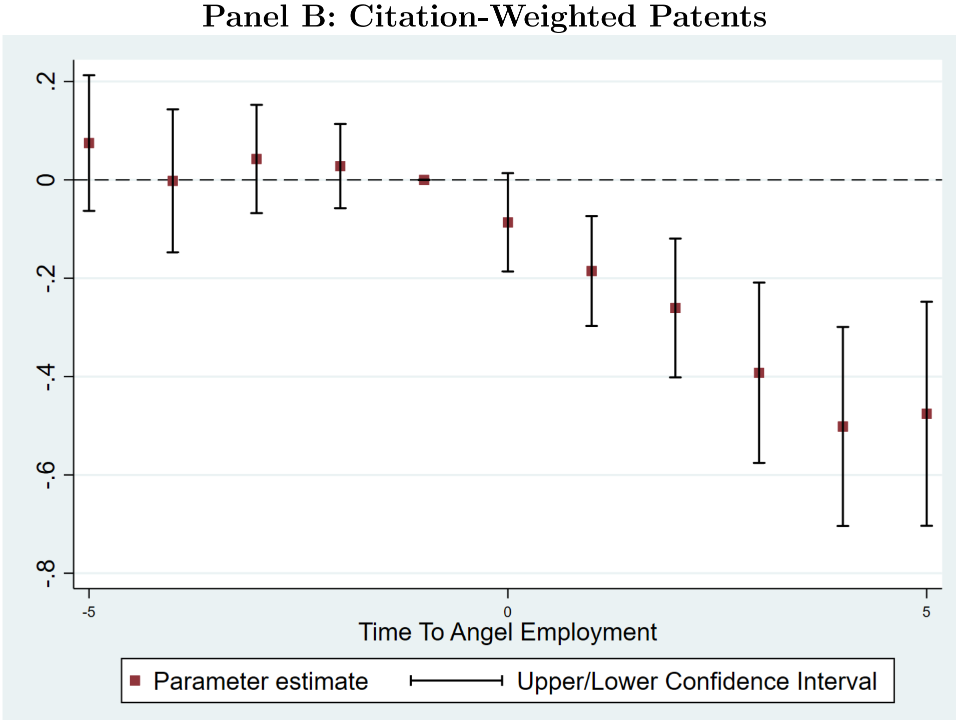


Table 5 – Pre-Trend: Propensity Score Matched Estimates
This table reports the result of the propensity score matched equation 3. The dependent variable in columns (1) and (2) is the economic value of patents in the next year following Kogan et al. (2017). Columns (3) and (4) are truncation-adjusted citation-weighted patents. The independent variable of interest is $AngelEmployeeDummy \times D_k$, where The variable of interest $AngelEmployeeDummy$ is equal to one if a firm has at least one angel employee. We estimate a propensity score in a logit regression including all controls, squared and cubed terms as well as simple interactions. Control firms are the three nearest neighbors and we match with replacement. Control and treatment firms have been normalized to event time in a difference-in-differences framework. The regression includes 8 time dummies (D_k), 4 pre- and 4 post-event. These dummies are interacted with the treatment dummy. The point estimates have been estimated using year $t = -1$ as the baseline year. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	(1)	(2)	(3)	(4)
	Economic Value	Economic Value	Citation-Weighted	Citation-Weighted
Angel Employee Dummy $\times D_{-4}$	0.03*	0.02	0.06	0.06
	(1.70)	(1.42)	(0.80)	(0.85)
Angel Employee Dummy $\times D_{-3}$	0.02	0.02	0.02	0.04
	(1.18)	(1.16)	(0.34)	(0.59)
Angel Employee Dummy $\times D_{-2}$	-0.00	0.00	0.01	0.03
	(-0.09)	(0.00)	(0.29)	(0.63)
Angel Employee Dummy $\times D_{-1}$	.	.	.	.
Angel Employee Dummy $\times D_{0}$	-0.03**	-0.03**	-0.05	-0.05
	(-2.08)	(-2.16)	(-0.76)	(-0.84)
Angel Employee Dummy $\times D_{+1}$	-0.04***	-0.04***	-0.13*	-0.14**
	(-2.69)	(-3.02)	(-1.86)	(-2.07)
Angel Employee Dummy $\times D_{+2}$	-0.04**	-0.04***	-0.20**	-0.20**
	(-2.56)	(-2.81)	(-2.30)	(-2.35)
Angel Employee Dummy $\times D_{+3}$	-0.06***	-0.06***	-0.29***	-0.30***
	(-2.84)	(-3.02)	(-2.77)	(-2.86)
N	7,913	7,913	8,091	8,091
R-squared	0.58	0.60	0.85	0.85
Controls	NO	YES	NO	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Table 6 – Instrumental Variable Regression

This table reports the result of the instrumental variable regression. The dependent variable in the second stage regression in columns (1) - (5) is the economic value of patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We instrument $AngelEmployeeDummy$, which is equal to one if a firm has at least one angel employee in the year. The instrument is the staggered implementation of prudent investor rules (PIR) across US states following (González-Uribe (2020)) interacted with VC fundraising on a state and year level. To better capture competition, we limit ourselves to small-VC funds with an average investment amount of less than 5$ Million USD. The Kleibergen-Paap F statistic from the first stage is reported. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm and state. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	ANG_{t+1}	ANG_{t+2}	ANG_{t+3}	ANG_{t+4}	ANG_{t+5}
Panel A: First Stage					
Instrument	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(-4.04)	(-3.46)	(-4.32)	(-3.81)	(-5.01)
F-Stat	16.33	18.67	25.10	42.89	40.14
Panel B: Second Stage					
	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
$AngelEmpl\hat{o}yeeDummy$	-2.30**	-1.54***	-1.29***	-0.81***	-0.69***
	(-4.25)	(-3.97)	(-3.69)	(-2.85)	(-3.51)
N	41,104	37,582	34,092	29,520	25,596
Other Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 7 – Angel Heterogeneity
This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents scaled by assets (Kogan et al. (2017)) over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. The independent variable of interest is the log plus one of the total number of angel employees at a firm. In Panel A, *Innovation-Related* is the total number of angels which among others have the following words in their job title: "product", "innov", "research", etc. Non-Innovation-Related angels includes angels in non-innovation related tasks such as "legal", "finance", etc. In Panel B we split angels into CEOs and board members and all other employees. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Panel A: Innovation and Non-Innovation Angels					
Innovation-Related Angels	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(-5.73)	(-6.14)	(-6.12)	(-5.10)	(-4.76)
Non-Innovation-Related Angels	-0.04**	-0.03	-0.03*	-0.03*	-0.05*
	(-2.38)	(-1.26)	(-1.69)	(-1.70)	(-1.93)
Panel B: CEO, Board Members, Other Employees					
CEO and Board Members	-0.03***	-0.03***	-0.04***	-0.04***	-0.04***
	(-2.79)	(-3.84)	(-4.42)	(-3.86)	(-3.27)
Other Employees	-0.05***	-0.04***	-0.05***	-0.04***	-0.04***
	(-4.36)	(-4.35)	(-5.15)	(-3.76)	(-3.12)

Table 8 – Effect of Successful Start-ups
This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents scaled by assets (Kogan et al. (2017)) over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. The independent variable of interest is the log plus one of the total number of angel investments at a firm. We group the number of linked start-ups depending on whether they ultimately failed or not by the end of 2019. The independent variables are the natural logarithm of one plus the number of failed and non-failed start-ups. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Failed Start-ups	-0.02**	-0.03**	-0.02**	-0.02**	-0.02**
	(-2.50)	(-2.17)	(-2.05)	(-2.18)	(-2.57)
Non-Failed Start-ups	-0.05***	-0.08***	-0.07***	-0.06***	-0.07***
	(-5.76)	(-4.35)	(-5.77)	(-5.06)	(-4.88)
Other Controls	YES	YES	YES	YES	YES
Firm and Year FE	YES	YES	YES	YES	YES

Table 9 – Effect of Angel Employees on Start-up Success

This table reports the result of a fixed effect regression showing the relationship between angel employee participation and start-up success. The variable of interest $AngelEmployeeDummy$ is equal to one if an angel employee invests in a start-up. The data contains all angel-financed start-ups. The dependent variable in columns (1) to (3) is whether the start-up successfully exited as measured by IPO, or M&A, either IPO or M&A. Columns (4) - (6) capture future start-up innovation as follows: (4) is a dummy set to one if the start-up is granted a patent. (5) is the log of total citations to all patents of the start-up. (6) is the log of the average citations per patent of the start-up. Control variables include the presence of a VC at an early stage, the age of the start-up, and the total funding amount in all funding rounds. All regressions include $City \times founding - Year$ fixed effects. Standard errors are clustered by City. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	(1)	(2)	(3)	(4)	(5)	(6)
	IPO	M&A	IPO or M&A	Patent Dummy	Start-up Citations	Citations per Patent
Angel Employee	0.01***	0.05***	0.06***	0.02***	0.10***	0.05***
	(2.94)	(7.18)	(7.70)	(3.33)	(4.21)	(3.71)
N	7,956	7,956	7,956	7,956	7,956	7,956
Controls	YES	YES	YES	YES	YES	YES
City-Year FE	YES	YES	YES	YES	YES	YES

Table 10 – Evidence from the SBJA Capital Gains Exemption
This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents scaled by assets (Kogan et al. (2017)) over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. The variable of interest is the interaction between *Treated* firms and *After*. *Treated* takes the value of 1 for any firm that has at least one angel employee investing in QSBS qualified start-ups following Edwards and Todtenhaupt (2020). *After* is a dummy equal to one for years after 2010. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Treated	-0.03*	-0.02	-0.02	-0.01	-0.01*
	(-2.01)	(-1.49)	(-1.28)	(-1.28)	(-1.72)
After#Treated	-0.01	-0.02*	-0.03**	-0.04***	-0.05***
	(-0.37)	(-1.75)	(-2.16)	(-3.04)	(-3.95)
Market Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-6.17)	(-7.09)	(-7.35)	(-5.57)	(-5.54)
R&D Expenditures	0.09***	0.06***	0.04**	0.02	-0.03
	(5.68)	(4.02)	(2.15)	(1.01)	(-1.49)
Tobin's Q	0.00***	0.00***	0.00*	0.00	0.00
	(5.46)	(3.12)	(1.94)	(0.03)	(0.76)
Profitability	0.00	0.00	0.00	-0.01	-0.01
	(0.20)	(0.84)	(0.54)	(-1.05)	(-1.40)
Tangibility	-0.00	-0.01	-0.01*	-0.01*	-0.02**
	(-0.55)	(-1.37)	(-1.65)	(-1.80)	(-2.15)
Age	0.00	0.00	0.00	0.00	0.00
	(0.71)	(1.17)	(1.28)	(0.57)	(0.36)
Herfindahl-Index	0.04*	0.03	0.02	0.03	0.04
	(1.68)	(1.42)	(1.05)	(1.38)	(1.59)
Herfindahl-Index Squared	-0.02	-0.02	-0.01	-0.02	-0.03
	(-1.03)	(-0.74)	(-0.59)	(-1.23)	(-1.48)
Liquidity	-0.16***	-0.20***	-0.23***	-0.24***	-0.13***
	(-4.66)	(-6.32)	(-7.63)	(-7.56)	(-3.98)
Capital Expenditures	0.01	0.00	-0.00	0.01	0.03**
	(1.17)	(0.08)	(-0.16)	(1.36)	(1.98)
Leverage	0.00	0.00	0.00	0.00	0.00
	(0.18)	(0.12)	(0.40)	(0.64)	(0.16)
Financial Constraints	-0.00	-0.00**	-0.00**	-0.00*	-0.00
	(-1.54)	(-2.15)	(-2.05)	(-1.75)	(-0.73)
Patent Stock	-0.02***	-0.02***	-0.03***	-0.03***	-0.03***
	(-3.10)	(-2.99)	(-4.27)	(-3.31)	(-3.84)
Number of Employees	-0.02***	-0.01***	-0.01***	-0.01***	-0.01***
	(-4.10)	(-4.15)	(-3.58)	(-3.03)	(-2.72)
Corporate Venture Capital	0.01	0.01	0.01	0.02	0.02
	(0.85)	(0.51)	(0.51)	(1.07)	(1.36)
Observations	51,324	46,851	42,341	36,412	31,332
R-squared	0.69	0.70	0.69	0.70	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 11 – Explorative vs. Exploitative Innovation
This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents scaled by assets (Kogan et al. (2017)) over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We split the variable into explorative and exploitative patents according to Brav et al. (2018). The variable of interest $AngelEmployeeDummy$ is equal to one if a firm has at least one angel employee in the year. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$Explore_{t+1}$	$Explore_{t+2}$	$Explore_{t+3}$	$Explore_{t+4}$	$Explore_{t+5}$
Angel Employee Dummy	-0.02***	-0.04***	-0.07***	-0.08***	-0.11***
	(-5.10)	(-5.08)	(-4.98)	(-4.42)	(-4.21)
	$Exploit_{t+1}$	$Exploit_{t+2}$	$Exploit_{t+3}$	$Exploit_{t+4}$	$Exploit_{t+5}$
Angel Employee Dummy	0.00	0.00	-0.00	-0.00	-0.00
	(0.69)	(0.29)	(-0.35)	(-0.43)	(-0.57)

Table 12 – Hostile Takeover Threat, Angel Employees and Corporate Innovation
This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents scaled by assets (Kogan et al. (2017)) over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We control for the baseline effect of angel employees defined as the log plus one of the total number of angel employees at a firm. The variable of interest $AngelEmployeeDummy$ is equal to one if a firm has at least one angel employee in the year. The second variable is an interaction of the $AngelEmployeeDummy$ with a dummy variable indicating if a firm has higher than median value of hostile takeover threat following Cain et al. (2017) ($HighTakeOver$). The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm and state. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Angel Employee Dummy	-0.01	-0.02**	-0.02**	-0.01*	-0.02*
	(-1.62)	(-2.34)	(-2.65)	(-1.79)	(-1.71)
HighTakeOver#Angel Employee	-0.03*	-0.02	-0.02***	-0.02***	-0.02**
	(-1.86)	(-1.49)	(-2.76)	(-2.28)	(-2.05)
Size	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-3.88)	(-3.98)	(-4.45)	(-4.97)	(-4.56)
R&D Expenditures	0.10***	0.06***	0.04**	0.03*	-0.02**
	(4.81)	(5.21)	(2.57)	(1.94)	(-2.03)
Tobin's Q	0.01***	0.00***	0.00	-0.00	0.00
	(6.68)	(3.35)	(1.54)	(-0.38)	(0.72)
Profitability	0.00	0.01	0.00	-0.01	-0.01
	(0.59)	(0.80)	(0.46)	(-0.65)	(-1.45)
Tangibility	-0.01	-0.01**	-0.01**	-0.02**	-0.02*
	(-1.22)	(-2.24)	(-2.07)	(-2.15)	(-1.83)
Age	0.00	0.00	0.00	0.00	0.00
	(0.61)	(0.87)	(0.45)	(0.13)	(0.32)
Herfindahl-Index	0.04*	0.03	0.03	0.04**	0.05*
	(1.70)	(1.49)	(1.50)	(2.06)	(1.96)
Herfindahl-Index Squared	-0.02	-0.01	-0.01	-0.03*	-0.04*
	(-1.31)	(-0.89)	(-1.02)	(-1.98)	(-1.87)
Liquidity	-0.19***	-0.22***	-0.27***	-0.25***	-0.14***
	(-3.00)	(-3.39)	(-4.94)	(-5.51)	(-4.06)
Capital Expenditures	0.02**	0.00	0.00	0.02	0.04*
	(2.66)	(0.49)	(0.43)	(1.61)	(1.88)
Leverage	0.00	0.00	0.00	0.00	0.00
	(0.17)	(0.48)	(0.87)	(0.94)	(0.09)
Financial Constraints	-0.00*	-0.00**	-0.00**	-0.00**	-0.00
	(-1.95)	(-2.33)	(-2.41)	(-2.03)	(-1.25)
Patent Stock	-0.02**	-0.02***	-0.03***	-0.03***	-0.03***
	(-2.60)	(-4.60)	(-5.84)	(-3.63)	(-4.62)
Number of Employees	-0.01**	-0.01**	-0.01***	-0.01**	-0.01**
	(-2.12)	(-2.68)	(-2.76)	(-2.62)	(-2.26)
Corporate Venture Capital	0.00	-0.01	-0.01	0.00	0.01
	(0.17)	(-0.63)	(-0.68)	(0.23)	(0.65)
Observations	39,887	36,132	31,434	27,206	23,589
R-squared	0.67	0.67	0.69	0.70	0.70
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 13 – Robustness: Non-Patent Based Innovation Output

This table reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) are non-patent based variables over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. In Panel A, the dependent variable (*NPA*) is the natural logarithm of one plus the number of new product announcement of the firm. In Panel B, the dependent variable is the natural logarithm of one plus the total number of trademarks (TM) of the firm. In Panel C, the dependent variable is the natural logarithm of one plus the total number of scientific publications ($PUBS$) of the firm. The variable of interest $AngelEmployeeDummy$ is equal to one if a firm has at least one angel employee in the year. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are in parenthesis.

Panel A: Effect on New Product Announcements					
	NPA_{t+1}	NPA_{t+2}	NPA_{t+3}	NPA_{t+4}	NPA_{t+5}
Angel Employee Dummy	-0.05	-0.08**	-0.11***	-0.07	-0.10*
	(-1.56)	(-2.23)	(-4.05)	(-1.67)	(-1.94)
Panel B: Effect on Trademarks					
	TM_{t+1}	TM_{t+2}	TM_{t+3}	TM_{t+4}	TM_{t+5}
Angel Employee Dummy	-0.07**	-0.11**	-0.17***	-0.12**	-0.11***
	(-2.23)	(-2.85)	(-3.97)	(-2.31)	(-2.00)
Panel C: Effect on Scientific Publications					
	$PUBS_{t+1}$	$PUBS_{t+2}$	$PUBS_{t+3}$	$PUBS_{t+4}$	$PUBS_{t+5}$
Angel Employee Dummy	-0.02	-0.18***	-0.32***	-0.33***	-0.41***
	(-1.31)	(-2.64)	(-3.64)	(-3.12)	(-3.19)
Other Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 14 – Sub-sample Analysis: California & Massachusetts Firms
This table reports the result of our baseline fixed effect panel regression of equation 1. Panel A excludes firms headquartered in California (CA) and Massachusetts (MA). Panel B only considers firms headquartered in CA and MA. The dependent variable in columns (1) - (5) are non-patent based variables over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. The variable of interest $AngelEmployeeDummy$ is equal to one if a firm has at least one angel employee in the year. The regression includes 15 standard control variables. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Panel A: Excluding firms in California & Massachusetts					
Angel Employee Dummy	-0.04***	-0.03***	-0.03***	-0.03***	-0.03***
	(-4.93)	(-5.60)	(-6.10)	(-4.97)	(-5.23)
Observations	45,222	40,958	35,370	30,600	26,491
Panel B: Only firms in California & Massachusetts					
Angel Employee Dummy	-0.06***	-0.05***	-0.05***	-0.05***	-0.05***
	(-4.31)	(-4.62)	(-4.74)	(-3.99)	(-3.87)
Observations	10,134	8,990	7,624	6,486	5,597
Other Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table 15 – Citation Weighted Patents - Private Firms

This table reports the result of fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) are truncation-adjusted citation-weighted patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We adjust citations for year and technology class following Hall et al. (2005). The sample is composed of all private firms in the US obtained from ORBIS. We limit ourselves to firms with turnover of at least 10M$. Due to data availability of private firms, the regression does not include control variables. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Angel Employee Dummy	0.01	-0.04*	-0.08***	-0.08***	-0.13***
	(0.23)	(-1.95)	(-3.57)	(-3.55)	(-3.84)
Observations	2,349,209	2,338,687	2,323,400	2,146,491	1,970,683
R-squared	0.68	0.66	0.63	0.64	0.64
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

APPENDIX

A. Variable Definitions

This section provides the variable definitions. All variables are measured at an annual frequency. All continuous variables are winsorized at the 1% and 99% level.

1. *Number of Angel Employees* – Natural logarithm of one plus the total number of angel employees on a given firm-year level. The information is obtained from Crunchbase.
2. *INNOV* – Economic value of patents aggregated on a firm-year level. The variable is scaled by total assets following Kogan et al. (2017). The data is available from 1927-2019. Alternatively, we use truncation-adjusted citation weighted patents as in Hall et al. (2005). The information is obtained from the website of Noah Stoffman.
3. *Size* – Natural logarithm of the market value of the firm. The information is obtained from Compustat.
4. *R&D Expenditures* – Total R&D expense scaled by book value of assets. The information is obtained from Compustat.
5. *Tobin's Q* – Book value of assets (AT) + market capitalization (MC) - common equity value (CEQ) - balance sheet deferred taxes, if available (TXDB) / total assets (AT). The information is obtained from Compustat.
6. *Profitability* – Operating income scaled by book value of assets. The information is obtained from Compustat.
7. *Tangibility* – Property, plant and equipment scaled by book value of assets. The information is obtained from Compustat.
8. *Age* – Natural logarithm of the number of years the firm appears in Compustat.
9. *Herfindahl-Index (Squared)* – Industry competition as measured by the Herfindahl index (squared) defined over yearly sales in a 4-digit SIC code. The information is obtained from Compustat.
10. *Liquidity* – Stock liquidity measured as the daily mean bid-ask spread. The information is obtained from CRSP.
11. *Capital Expenditures* – Capital Expenditure scaled by the book value of the firm. The information is obtained from Compustat.

12. *Leverage* – Leverage ratio of the firm's total debt scaled by book value of assets. The information is obtained from Compustat.
13. *Financial Constraints* – Dummy variable indicating Financial Constraints if a firm is flagged as falling in the top tercile of the distribution of financial constraints every year by either of the measures proposed by Kaplan and Zingales (1997), Whited and Wu (2006) and Hadlock and Pierce (2010). The information is obtained from Compustat.
14. *Patent Stock* – Total number of patents assigned to a firm in the last 20 years (equivalent to patent expiry period). The information is obtained from the website of Noah Stoffman.
15. *Number of Employees* – Natural logarithm of the total number of employees. The information is obtained from Compustat.
16. *Corporate Venture Capital* – A dummy variable equal to one if the firm has an active corporate venture capital program. The variable was constructed following Ma (2020). The information is obtained from Refinitiv VentureXperts (formerly Thomson Reuters).
17. *small-VC fundraising* – The total amount of funds raised by small venture capital firms (in million US dollars) in the preceding year. We eliminate funds with average investments below 5M$. The information is obtained from Refinitiv Eikon (formerly Thomson Reuters).
18. *Trademarks* – The log of one plus the total amount of trademarks applied in a given year. We obtain trademarks linked to gvkeys from Heath and Mace (2020).
19. *Product Announcements* – The log of one plus the total amount of new product launches in a given year. We follow the methodology of Chu et al. (2020) and proxy for new product launches by screening the key developments (Compustat) database for the following keywords: "unveil", "launch", and "new product".
20. *Scientific Publications* – The log of one plus the total amount of scientific publications. We obtain the data from Arora et al. (2020). The variable is aggregated on a permno and year basis. We use version 7 (December 2020) available here: https://zenodo.org/record/4320782

B. Data Description

In the parts below, we provide more details on how we obtained the data used in this paper. We start with a more detailed description of the Crunchbase dataset and then explain how we obtained the employment histories from LinkedIn.

B.1. Crunchbase

Crunchbase was the starting point for our data collection. We obtained the data through a private API and used the bulk downloads. The relational database provides information on staged funding rounds, e.g. which company raised how many funds, who participated, and when the investment took place. We first merge the funding round data with information on investments, e.g. which investors participated in which funding round. This provides an overview of who invested in which funding round. Most of the investments are venture capital investments, so the next step is to obtain personal (angel) investments. We do this by merging the dataset with the people database. The people database covers more than 870,000 individuals that have connection to the start-up world. Most individuals in the database are founders, so they are not material to our research. We only keep investments that are tied to individuals. The next step is to limit the dataset to US individuals investing in US firms. Additionally, we manually verified our angel investors. E.g. we eliminated individuals tied to venture capital firms and individuals tied to a corporate venture capital arm of a firm.

Crunchbase also provides information on employment histories in the so-called jobs database. We can therefore see which individual worked in which firm. We initially used this data for preliminary results, but decided that the coverage was not sufficient. We therefore looked for an alternate database which provides more comprehensive employment histories.

B.2. Employment History

Crunchbase already provided links to individual LinkedIn profiles to the vast majority of investors in our sample. We manually verified whether these links were in fact correct and compared the employment history listed in Crunchbase with the history listed in LinkedIn. For the subset of individuals with missing LinkedIn links, we were able to collect the link for roughly 66% of the remaining subsample. We again verified whether we map the correct individual by comparing employment histories. As mentioned in the paper, we were left with a small set of individuals (who sometimes had many investments) without a LinkedIn profile. This could result in a substantial selection bias if high-level employees are less likely to have a LinkedIn profile. We thus ranked the sample by number of investments and manually obtained employment histories for all individuals with at least 3 angel investments. We were able to find employment information for 98% of all angel investments in our sample.

We also performed a number of cleaning exercises. One can in principle provide any information on LinkedIn. The information is self reported and not independently audited. We remove jobs when the job title refers to being an investor in the firm. For instance, many individuals claim to work for Tesla and state their position as "investor" or "shareholder". We remove these jobs from our data, as it is unlikely that these individuals are decision makers at that firm. Also, many start-up founders are stating their firm name as follows: FIRM NAME (acquired by ACQUIRER). We cleaned the employer name such to make sure that we do not falsely match an investor to a listed ACQUIRER. We performed a string search to look for instances of "M&A", "acquired", "acquisition", etc. to eliminate these instances.

Table A1 – Economic Value of Patents - Log Transformed Angel Employees
This reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. Economic value of patents is obtained from Kogan et al. (2017). The variable of interest - Number of Angel Employees - is defined as the log plus one of the total number of angel employees at a firm Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Number of Angel Employees	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(-5.85)	(-6.16)	(-6.15)	(-5.23)	(-5.02)
Market Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-7.99)	(-8.58)	(-8.03)	(-6.13)	(-5.80)
R&D Expenditures	0.07***	0.05***	0.04***	0.02	-0.02
	(5.58)	(3.84)	(2.91)	(1.47)	(-1.38)
Tobin's Q	0.00***	0.00***	0.00*	-0.00	0.00
	(7.21)	(4.81)	(1.71)	(-0.56)	(0.01)
Profitability	-0.00	-0.00	0.00	-0.01	-0.01**
	(-0.77)	(-0.25)	(0.01)	(-1.45)	(-2.48)
Tangibility	0.01**	0.01	0.00	0.00	0.00
	(2.00)	(1.30)	(0.77)	(0.56)	(0.27)
Age	0.00	0.00	0.00	0.00	-0.00
	(0.97)	(1.50)	(0.93)	(0.33)	(-0.11)
Herfindahl-Index	0.00	0.00	-0.00	0.01	0.01
	(0.17)	(0.05)	(-0.08)	(0.42)	(0.71)
Herfindahl-Index Squared	0.01	0.01	0.01	0.00	-0.01
	(0.44)	(0.58)	(0.71)	(0.04)	(-0.41)
Liquidity	-0.16***	-0.18***	-0.18***	-0.19***	-0.12***
	(-5.61)	(-6.77)	(-7.71)	(-7.51)	(-4.58)
Capital Expenditures	0.00	-0.01	-0.01	0.01	0.01
	(0.36)	(-1.00)	(-1.06)	(0.91)	(1.25)
Leverage	-0.00	-0.00	0.00	0.00	0.00
	(-0.52)	(-0.15)	(0.55)	(0.59)	(0.38)
Financial Constraints	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.97)	(-1.09)	(-1.57)	(-1.10)	(-0.73)
Patent Stock	-0.04***	-0.04***	-0.04***	-0.04***	-0.05***
	(-6.92)	(-6.27)	(-6.04)	(-5.30)	(-5.72)
Number of Employees	-0.01***	-0.01***	-0.01***	-0.01**	-0.00**
	(-3.26)	(-3.16)	(-2.86)	(-2.44)	(-2.05)
Corporate Venture Capital	0.03*	0.02	0.01	0.02	0.02
	(1.84)	(1.36)	(0.92)	(1.31)	(1.51)
Observations	54,514	49,162	42,341	36,412	31,332
R-squared	0.67	0.67	0.69	0.70	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A2 – **Economic Value of Patents - Only Firms with Angel Employees**
This reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. Economic value of patents is obtained from Kogan et al. (2017). The dependent variable is the number of angel employees for a firm in a given year. The sample is composed of only firms that have angel employees at one point in time. Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Number of Angel Employees	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(-3.76)	(-3.76)	(-3.94)	(-3.18)	(-3.21)
Market Value	-0.02**	-0.02***	-0.02***	-0.02***	-0.02***
	(-2.44)	(-3.34)	(-3.47)	(-3.45)	(-2.89)
R&D Expenditures	0.11**	0.00	-0.03	-0.07	-0.09
	(2.00)	(0.03)	(-0.42)	(-1.08)	(-1.48)
Tobin's Q	0.01***	0.01***	0.01***	0.00	0.00*
	(4.35)	(4.28)	(2.65)	(1.57)	(1.71)
Profitability	0.01	-0.03	-0.03	-0.04	-0.03
	(0.30)	(-1.25)	(-1.06)	(-1.08)	(-1.11)
Tangibility	0.07	0.05	-0.00	0.03	-0.00
	(1.27)	(0.78)	(-0.08)	(0.56)	(-0.07)
Age	0.03***	0.03***	0.02***	0.02**	0.02**
	(4.05)	(3.87)	(2.96)	(2.21)	(2.11)
Herfindahl-Index	-0.03	-0.06	-0.08	-0.05	-0.04
	(-0.21)	(-0.61)	(-0.77)	(-0.54)	(-0.46)
Herfindahl-Index Squared	0.10	0.12	0.13	0.09	0.05
	(0.71)	(0.96)	(1.23)	(0.97)	(0.71)
Liquidity	-0.97**	-1.23***	-1.42***	-1.45***	-0.97***
	(-2.51)	(-3.44)	(-3.86)	(-4.07)	(-3.36)
Capital Expenditures	0.00	-0.07	0.06	0.10	0.15**
	(0.01)	(-0.74)	(0.80)	(1.32)	(2.04)
Leverage	-0.01	-0.00	-0.01	0.01	0.02
	(-0.24)	(-0.03)	(-0.34)	(0.46)	(0.92)
Financial Constraints	-0.02**	-0.01**	-0.01**	-0.01*	-0.00
	(-2.29)	(-2.17)	(-2.43)	(-1.91)	(-0.21)
Patent Stock	-0.08**	-0.09**	-0.08**	-0.07	-0.07
	(-2.32)	(-2.30)	(-1.97)	(-1.54)	(-1.30)
Number of Employees	-0.04***	-0.03***	-0.03***	-0.02**	-0.02*
	(-3.39)	(-3.31)	(-2.76)	(-1.99)	(-1.66)
Corporate Venture Capital	0.01	0.00	-0.01	-0.02	-0.02
	(0.26)	(0.04)	(-0.38)	(-0.67)	(-1.03)
Observations	4,243	3,998	3,518	3,095	2,741
R-squared	0.72	0.72	0.73	0.74	0.75
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A3 – **Economic Value of Patents - Only Firms that Patent**

This reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. Economic value of patents is obtained from Kogan et al. (2017). The dependent variable is the number of angel employees for a firm in a given year. The sample is composed of only firms that patent at one point in time. Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Number of Angel Employees	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(-5.04)	(-5.29)	(-5.37)	(-4.49)	(-4.43)
Market Value	-0.02***	-0.02***	-0.02***	-0.02***	-0.02***
	(-7.74)	(-8.54)	(-8.05)	(-6.32)	(-6.13)
R&D Expenditures	0.08***	0.05***	0.04**	0.01	-0.04**
	(4.49)	(3.09)	(2.21)	(0.54)	(-2.36)
Tobin's Q	0.01***	0.00***	0.00**	-0.00	0.00
	(7.34)	(5.02)	(2.24)	(-0.07)	(0.31)
Profitability	-0.00	0.00	0.00	-0.01	-0.02**
	(-0.31)	(0.43)	(0.51)	(-1.34)	(-2.36)
Tangibility	-0.00	-0.01	-0.01	-0.01	-0.02
	(-0.01)	(-0.42)	(-0.85)	(-1.10)	(-1.47)
Age	-0.00	-0.00	-0.01	-0.01*	-0.01**
	(-1.11)	(-1.03)	(-1.46)	(-1.83)	(-2.18)
Herfindahl-Index	0.02	0.03	0.02	0.04	0.05
	(0.48)	(0.72)	(0.71)	(1.11)	(1.33)
Herfindahl-Index Squared	0.01	-0.00	-0.00	-0.02	-0.03
	(0.15)	(-0.03)	(-0.11)	(-0.75)	(-1.18)
Liquidity	-0.24***	-0.33***	-0.35***	-0.37***	-0.21***
	(-2.94)	(-4.60)	(-5.77)	(-5.97)	(-3.42)
Capital Expenditures	0.03	-0.01	-0.02	0.03	0.05*
	(0.96)	(-0.38)	(-0.95)	(1.10)	(1.91)
Leverage	-0.01	-0.00	0.01	0.01	0.01
	(-0.61)	(-0.09)	(0.67)	(0.87)	(0.54)
Financial Constraints	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.95)	(-1.17)	(-1.60)	(-0.87)	(-0.35)
Patent Stock	-0.04***	-0.04***	-0.04***	-0.04***	-0.04***
	(-7.32)	(-6.49)	(-6.00)	(-4.93)	(-5.30)
Number of Employees	-0.02***	-0.02***	-0.02***	-0.01***	-0.01**
	(-3.72)	(-3.60)	(-3.20)	(-2.77)	(-2.48)
Corporate Venture Capital	0.03*	0.02	0.01	0.02	0.02
	(1.74)	(1.17)	(0.73)	(1.07)	(1.23)
Observations	25,994	24,100	21,333	18,758	16,456
R-squared	0.65	0.66	0.68	0.69	0.70
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A4 – Economic Value of Patents - Only Firms with Angel Employees
This reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) is the economic value of patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. Economic value of patents is obtained from Kogan et al. (2017). The dependent variable has been transformed using a inverse hyperbolic sine transformation as follows: $log(y_i+(y_i^2+1)^{1/2})$. The independent variable is the number of angel employees for a firm in a given year. The sample is composed of only firms that have angel employees at one point in time. Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Number of Angel Employees	-0.05***	-0.05***	-0.05***	-0.05***	-0.05***
	(-5.85)	(-6.16)	(-6.15)	(-5.23)	(-5.02)
Market Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-7.99)	(-8.58)	(-8.03)	(-6.13)	(-5.80)
R&D Expenditures	0.07***	0.05***	0.04***	0.02	-0.02
	(5.58)	(3.84)	(2.91)	(1.47)	(-1.38)
Tobin's Q	0.00***	0.00***	0.00*	-0.00	0.00
	(7.21)	(4.81)	(1.71)	(-0.56)	(0.01)
Profitability	-0.00	-0.00	0.00	-0.01	-0.01**
	(-0.77)	(-0.25)	(0.01)	(-1.45)	(-2.48)
Tangibility	0.01**	0.01	0.00	0.00	0.00
	(2.00)	(1.30)	(0.77)	(0.56)	(0.27)
Age	0.00	0.00	0.00	0.00	-0.00
	(0.97)	(1.50)	(0.93)	(0.33)	(-0.11)
Herfindahl-Index	0.00	0.00	-0.00	0.01	0.01
	(0.17)	(0.05)	(-0.08)	(0.42)	(0.71)
Herfindahl-Index Squared	0.01	0.01	0.01	0.00	-0.01
	(0.44)	(0.58)	(0.71)	(0.04)	(-0.41)
Liquidity	-0.16***	-0.18***	-0.18***	-0.19***	-0.12***
	(-5.61)	(-6.77)	(-7.71)	(-7.51)	(-4.58)
Capital Expenditures	0.00	-0.01	-0.01	0.01	0.01
	(0.36)	(-1.00)	(-1.06)	(0.91)	(1.25)
Leverage	-0.00	-0.00	0.00	0.00	0.00
	(-0.52)	(-0.15)	(0.55)	(0.59)	(0.38)
Financial Constraints	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.97)	(-1.09)	(-1.57)	(-1.10)	(-0.73)
Patent Stock	-0.04***	-0.04***	-0.04***	-0.04***	-0.05***
	(-6.92)	(-6.27)	(-6.04)	(-5.30)	(-5.72)
Number of Employees	-0.01***	-0.01***	-0.01***	-0.01**	-0.00**
	(-3.26)	(-3.16)	(-2.86)	(-2.44)	(-2.05)
Corporate Venture Capital	0.03*	0.02	0.01	0.02	0.02
	(1.84)	(1.36)	(0.92)	(1.31)	(1.51)
Observations	54,514	49,162	42,341	36,412	31,332
R-squared	0.67	0.67	0.69	0.70	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Figure A3 – Plotting Raw Data
This figure plots raw data. Observations are grouped according to the log number of angel employees. The variable of interest, the economic value of patents is the mean within each group. The data shows the residuals from a regression of the economic value of patent following Kogan et al. (2017) after a regression only only on firm fixed effects.

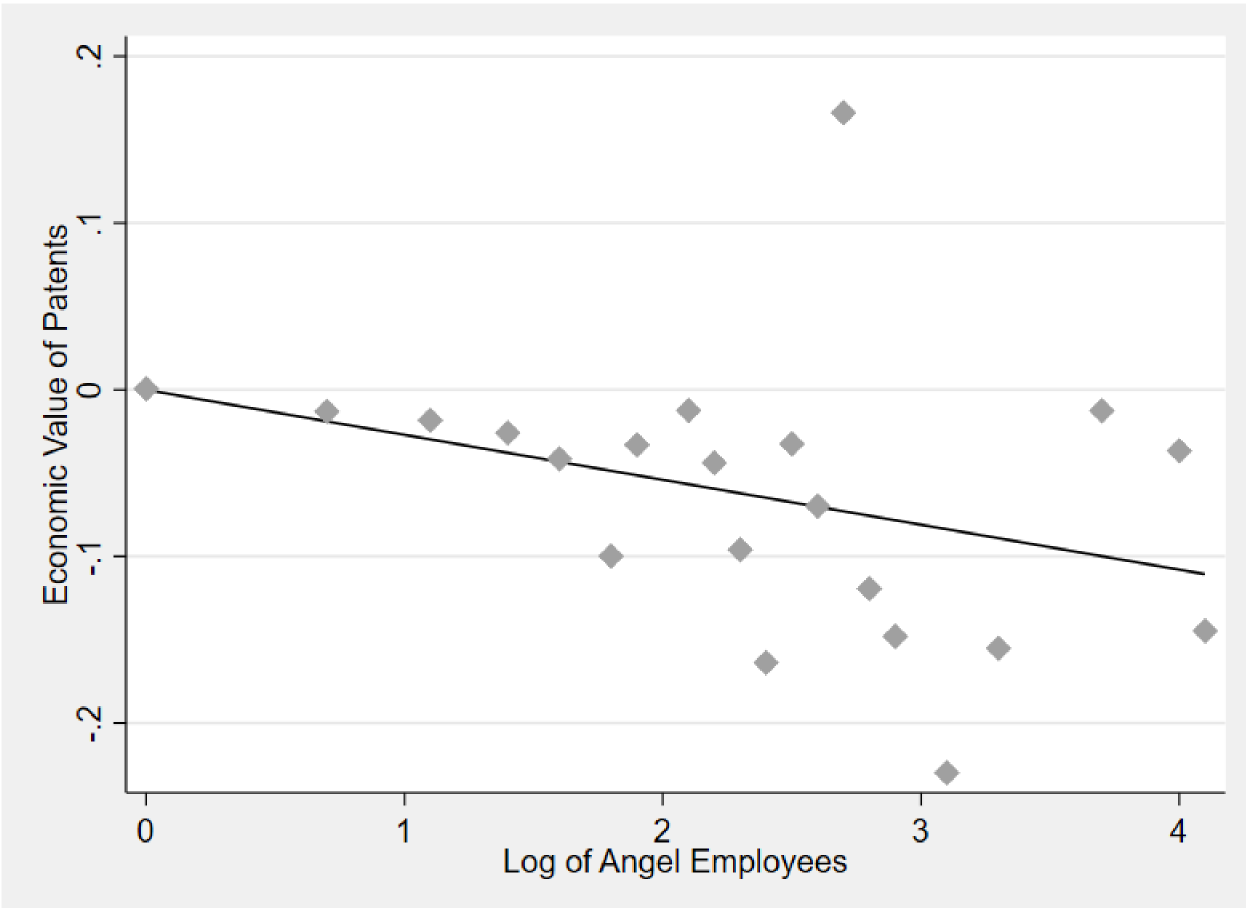


Table A5 – Citation-Weighted Patents – Log Transformed Angel Employees

This table reports the result of fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) are truncation-adjusted citation-weighted patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We adjust the citations for year and technology class following Hall et al. (2005). Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Number of Angel Employees	-0.23***	-0.41***	-0.67***	-0.66***	-0.74***
	(-4.95)	(-7.05)	(-8.62)	(-7.12)	(-7.18)
Market Value	0.02*	-0.01	-0.02*	-0.03**	-0.04***
	(1.93)	(-0.58)	(-1.77)	(-2.23)	(-3.26)
R&D Expenditures	0.15**	0.09	0.06	-0.08	-0.03
	(2.38)	(1.31)	(0.66)	(-0.85)	(-0.35)
Tobin's Q	0.01***	0.01**	0.01*	0.01**	0.02***
	(2.71)	(2.53)	(1.68)	(2.09)	(2.91)
Profitability	-0.05*	-0.04	-0.02	-0.02	0.01
	(-1.93)	(-1.33)	(-0.56)	(-0.68)	(0.22)
Tangibility	0.03	0.04	0.04	0.05	0.09
	(0.65)	(0.83)	(0.86)	(0.79)	(1.42)
Age	0.03**	0.06***	0.08***	0.10***	0.10***
	(2.57)	(4.32)	(5.03)	(5.23)	(4.93)
Herfindahl-Index	0.16	0.04	0.07	0.11	0.18
	(0.90)	(0.23)	(0.31)	(0.46)	(0.71)
Herfindahl-Index Squared	-0.04	0.06	0.03	-0.00	-0.06
	(-0.23)	(0.38)	(0.13)	(-0.01)	(-0.28)
Liquidity	-0.93***	-1.21***	-1.50***	-1.34***	-1.04***
	(-4.55)	(-5.83)	(-6.28)	(-4.88)	(-3.24)
Capital Expenditures	0.12**	0.03	0.07	0.06	0.05
	(2.14)	(0.59)	(1.13)	(0.83)	(0.72)
Leverage	-0.10***	-0.11***	-0.11***	-0.07*	-0.04
	(-3.16)	(-3.36)	(-2.90)	(-1.74)	(-0.88)
Financial Constraints	-0.01*	-0.03***	-0.02**	-0.01	-0.00
	(-1.70)	(-2.92)	(-2.19)	(-1.31)	(-0.42)
Patent Stock	-0.38***	-0.34***	-0.30***	-0.22***	-0.20***
	(-8.27)	(-6.59)	(-5.29)	(-3.83)	(-3.04)
Number of Employees	0.08***	0.04*	0.01	-0.02	-0.04
	(3.67)	(1.89)	(0.43)	(-0.71)	(-1.41)
Corporate Venture Capital	0.23**	0.31***	0.43***	0.43***	0.46***
	(2.53)	(2.76)	(3.13)	(2.97)	(2.86)
Observations	57,051	57,051	57,051	57,051	57,051
R-squared	0.83	0.80	0.77	0.74	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A6 – **Citation-Weighted Patents - Dummy Variable Regression**

This reports the result of our baseline fixed effect panel regression of equation 1. The dependent variable in columns (1) - (5) are truncation-adjusted citation-weighted patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We adjust the citations for year and technology class following Hall et al. (2005). The variable of interest - Angel Employees - has been defined as a dummy equal to one if a firm employs an angel investor in a particular year. Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Angel Employee Dummy	-0.13***	-0.27***	-0.45***	-0.43***	-0.48***
	(-2.71)	(-4.89)	(-6.38)	(-5.22)	(-5.24)
Market Value	0.05***	0.03***	0.01	0.01	-0.00
	(6.04)	(3.06)	(1.25)	(0.65)	(-0.28)
R&D Expenditures	0.08**	0.07***	0.02	0.06*	0.01
	(2.52)	(2.70)	(0.36)	(1.67)	(0.44)
Tobin's Q	0.00	0.00	-0.00	0.00	0.00
	(0.89)	(0.38)	(-0.26)	(0.53)	(1.56)
Profitability	-0.01	-0.01	-0.03	-0.01	-0.02
	(-0.56)	(-1.03)	(-1.07)	(-1.24)	(-1.50)
Tangibility	0.04	0.04	0.05	0.03	0.09
	(0.89)	(0.81)	(0.96)	(0.56)	(1.37)
Age	0.02	0.05***	0.08***	0.10***	0.10***
	(1.63)	(3.56)	(4.59)	(4.90)	(4.68)
Herfindahl-Index	0.19	0.06	0.08	0.13	0.17
	(1.05)	(0.32)	(0.33)	(0.53)	(0.65)
Herfindahl-Index Squared	-0.05	0.06	0.03	-0.01	-0.05
	(-0.31)	(0.34)	(0.14)	(-0.05)	(-0.22)
Liquidity	-0.43**	-0.52**	-0.66**	-0.53**	-0.34*
	(-2.55)	(-2.37)	(-2.36)	(-2.15)	(-1.76)
Capital Expenditures	0.10**	0.04	0.05	0.02	0.01
	(2.29)	(0.90)	(0.96)	(0.42)	(0.12)
Leverage	-0.07***	-0.11***	-0.11***	-0.08**	-0.06
	(-2.76)	(-3.92)	(-3.47)	(-2.14)	(-1.42)
Financial Constraints	-0.01*	-0.03***	-0.02**	-0.02	-0.01
	(-1.67)	(-2.90)	(-2.38)	(-1.40)	(-0.44)
Patent Stock	-0.09***	-0.09***	-0.09***	-0.08***	-0.06**
	(-5.33)	(-5.37)	(-3.67)	(-2.81)	(-2.51)
Number of Employees	0.07***	0.02	-0.02	-0.05*	-0.08***
	(3.04)	(0.87)	(-0.70)	(-1.88)	(-2.73)
Corporate Venture Capital	0.23**	0.33***	0.46***	0.46***	0.48***
	(2.34)	(2.79)	(3.25)	(3.06)	(2.89)
Observations	57,051	57,051	57,051	57,051	57,051
R-squared	0.84	0.81	0.78	0.74	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A7 – Angel Employees and R&D Expenses

This reports the result of fixed effect panel regression of where the dependent variable in columns (1) - (5) is the R&D expenses of a firm scaled by the book value of assets over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. The variable of interest is *Angel Employee Dummy* which is equal to one if a firm employs at least one angel investor in a particular year. Variable definitions are provided in Section 1 of the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$R\&D_{t+1}$	$R\&D_{t+2}$	$R\&D_{t+3}$	$R\&D_{t+4}$	$R\&D_{t+5}$
Angel Employee Dummy	0.004	0.003	0.000	0.001	0.004
	(1.40)	(0.96)	(0.29)	(0.39)	(1.04)
Observations	51,324	43,814	37,464	32,055	27,284
R-squared	0.84	0.81	0.78	0.74	0.71
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A8 – Instrumental Variable Regression with Citation Weighted Patents
This table reports the result of second stage of the instrumental variable regression. Panel A of the table provides the details of the first stage regression. The dependent variable is the number of angel employees for a firm in a given year. Panel B presents the second stage regression results. The dependent variable in columns (1) - (5) are the truncation adjusted citation weighted patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. We adjust the citations for year and technology class following Hall et al. (2005). Variable definitions are provided in Section 1 of the Appendix. All regressions include firm, state, and Year fixed effects. Standard errors are clustered by firm and state. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Number of Angel Employees	-5.37***	-3.11*	-6.27***	-6.45***	-6.38***
	(-3.38)	(-1.77)	(-3.44)	(-4.15)	(-3.24)
First Stage F-Stat	25.48	23.48	24.23	56.14	24.65
Observations	41,102	37,580	34,089	29,517	25,593
Other Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Table A9 – Effect of Large VC fund raising

This table reports an out of sample test of the exclusion restriction on the IV regression. The dependent variable in columns (1) - (5) is the economic value of patents over the subsequent k years ($INNOV_{t+k}$), where $k = [1, 5]$, respectively. Economic value of patents is obtained from Kogan et al. (2017). The dependent variable is fund raising of large VC funds. Large VC funds are defined to invest more than 5M$ per investment on average. Variable definitions are provided in Section 1 of the Appendix. All regressions include firm, state, and Year fixed effects. Standard errors are clustered by firm and state. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$INNOV_{t+1}$	$INNOV_{t+2}$	$INNOV_{t+3}$	$INNOV_{t+4}$	$INNOV_{t+5}$
Large VC	0.00***	0.00**	-0.00	-0.00	0.00
	(5.10)	(2.36)	(-0.34)	(-0.60)	(0.46)
Market Value	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-3.48)	(-3.75)	(-4.20)	(-5.17)	(-4.64)
R&D Expenditures	0.09***	0.06***	0.04**	0.02	-0.03***
	(4.01)	(4.81)	(2.34)	(1.60)	(-2.82)
Tobin's Q	0.01***	0.00***	0.00*	0.00	0.00
	(7.42)	(3.75)	(1.77)	(0.34)	(1.28)
Profitability	0.00	0.00	0.00	-0.01	-0.01*
	(0.20)	(0.64)	(0.32)	(-0.66)	(-1.77)
Tangibility	-0.01	-0.01**	-0.01**	-0.02**	-0.02*
	(-1.14)	(-2.28)	(-2.17)	(-2.37)	(-1.81)
Age	0.00	0.00*	0.00*	0.00	0.00
	(1.63)	(1.80)	(1.91)	(1.05)	(0.63)
Herfindahl-Index	0.05	0.04	0.03	0.04	0.04
	(1.59)	(1.59)	(1.21)	(1.66)	(1.62)
Herfindahl-Index Squared	-0.03	-0.02	-0.01	-0.03	-0.03
	(-1.49)	(-1.20)	(-0.84)	(-1.62)	(-1.54)
Liquidity	-0.17**	-0.21***	-0.24***	-0.23***	-0.12***
	(-2.62)	(-3.28)	(-4.21)	(-4.43)	(-3.37)
Capital Expenditures	0.02*	0.00	0.00	0.02*	0.03
	(1.93)	(0.22)	(0.04)	(1.78)	(1.63)
Leverage	0.00	0.00	0.00	0.00	-0.00
	(0.60)	(0.67)	(0.38)	(0.15)	(-0.72)
Financial Constraints	-0.00*	-0.00**	-0.00**	-0.00**	-0.00
	(-1.81)	(-2.23)	(-2.34)	(-2.01)	(-0.85)
Patent Stock	-0.02**	-0.02***	-0.03***	-0.03***	-0.04***
	(-2.41)	(-4.00)	(-5.68)	(-4.06)	(-4.96)
Number of Employees	-0.02**	-0.01**	-0.01**	-0.01**	-0.01*
	(-2.06)	(-2.40)	(-2.40)	(-2.23)	(-1.75)
Corporate Venture Capital	0.01	0.00	-0.00	0.00	0.01
	(0.69)	(0.04)	(-0.11)	(0.26)	(0.50)
Observations	36,892	33,677	30,514	26,377	22,877
R-squared	0.70	0.71	0.70	0.72	0.72
Other Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES

Figure A4 – Covariate Balance Before and After Matching
This figure visualizes covariate balance before and after propensity score matching. The x-axis shows the bias between the treated and the control firms on various covariates. The matching statistics table in the main paper only showed the simple control variables. This graph shows all variables included in the model. We have more than 100 variables including: all simple controls, squared, and cubed terms, as well as simple interactions between all controls. The figure shows that we achieve significant covariate balance over the variables included in the model.

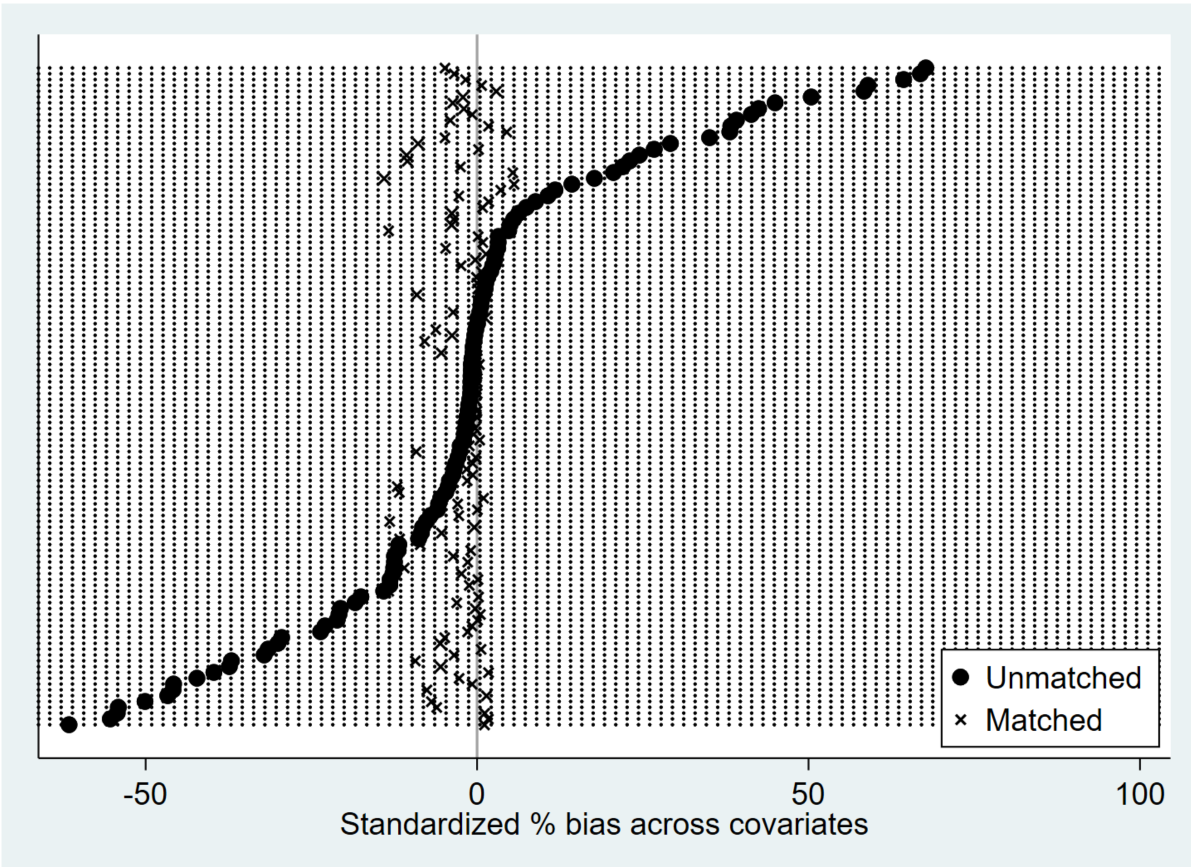


Figure A5 – PSM: Model selection
This Figure visualizes the robustness of model selection of the propensity score regression following DeFond et al. (2017). The figure shows 3000 random model specifications. In each instance, we draw a random number of nearest neighbors between 1 and 3 and a random subset of 115 variables to compute the propensity score. The figure visualizes the coefficients from these 3000 random specifications. For simplification, the coefficients are collapsed into one POST*TREATED coefficient. The red reference line indicates our estimated coefficient.

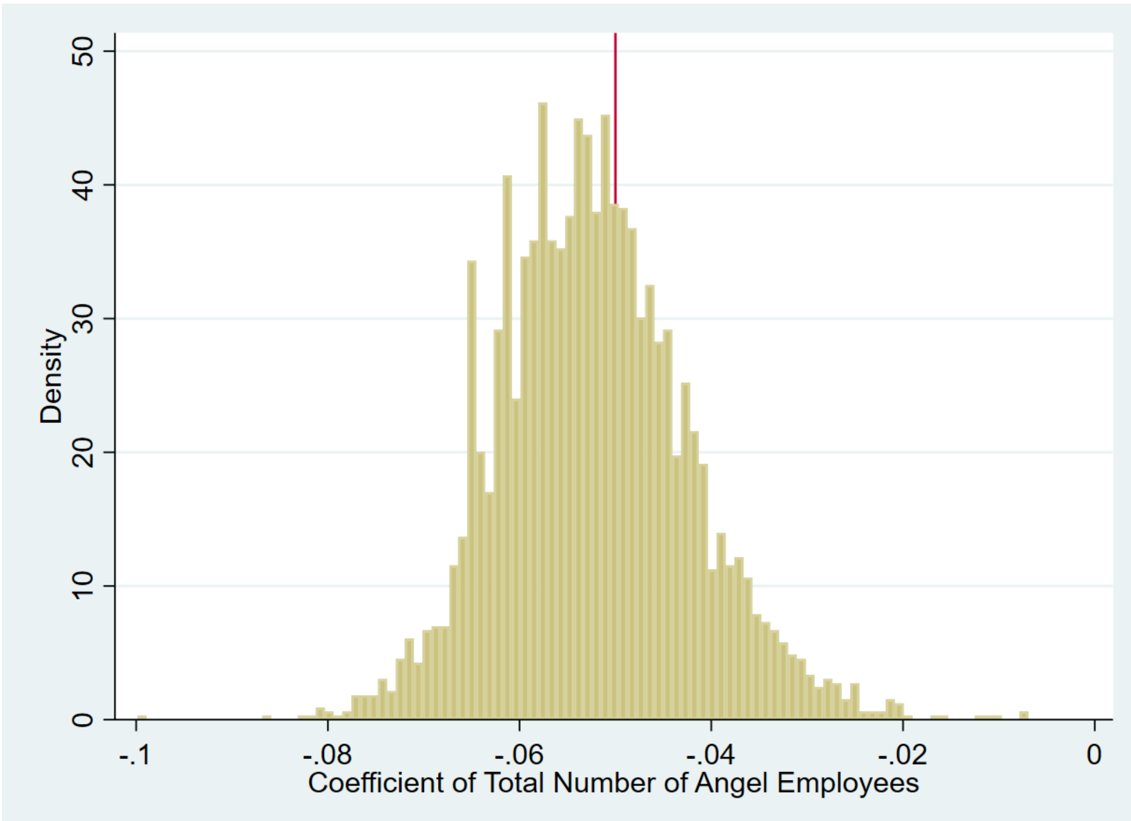


Table A10 – Governance, Exploratory Patents and Angel Employees

This table reports the result of fixed effect panel regression of the model in equation 1 by interacting *Number of Angels* with a dummy variable indicating if a firm has higher than median value of hostile takeover threat as developed in Cain et al. (2017). The dependent variable in columns (1) - (3) is the economic value of exploratory patents over the subsequent k years ($EXPLR_{t+k}$), where $k = [3, 5]$, respectively. The dependent variable in columns (4) - (6) is the economic value of exploitative patents over the subsequent k years ($EXPLT_{t+k}$), where $k = [3, 5]$, respectively. Economic value of patents is measured following Kogan et al. (2017). The independent variable of interest is the log plus one of the total number of angel employees at a firm. Variable definitions are provided in the Appendix. All regressions include Firm and Year fixed effects. Standard errors are clustered by firm and state. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. t-statistics are displayed in parenthesis.

	$EXPLR_{t+3}$	$EXPLR_{t+4}$	$EXPLR_{t+5}$	$EXPLT_{t+3}$	$EXPLT_{t+4}$	$EXPLT_{t+5}$
Number of Angel Employees	-0.06***	-0.07***	-0.10***	-0.00	-0.00*	-0.01***
	(-2.68)	(-2.73)	(-2.68)	(-0.96)	(-1.93)	(-2.68)
HighTakeOver#Angel Employees	-0.07***	-0.09***	-0.10**	0.00	0.00**	0.01**
	(-3.29)	(-2.83)	(-2.13)	(1.43)	(2.01)	(2.05)
Size	-0.04***	-0.04***	-0.05***	0.00	0.00	0.00
	(-4.26)	(-4.43)	(-4.58)	(0.14)	(0.65)	(1.02)
R&D Expenditures	0.15***	0.18***	0.16***	0.01*	0.01*	0.01*
	(6.11)	(5.04)	(3.60)	(1.84)	(1.82)	(1.82)
Tobin's Q	0.01***	0.01***	0.01***	0.00	-0.00	-0.00
	(3.72)	(2.78)	(3.03)	(0.47)	(-0.26)	(-0.22)
Profitability	-0.01	-0.03	-0.04	0.00	0.00*	0.00**
	(-0.60)	(-1.21)	(-1.30)	(1.47)	(1.92)	(2.32)
Tangibility	-0.02	-0.04*	-0.06**	0.00	0.00	0.00
	(-1.47)	(-1.68)	(-2.13)	(0.03)	(0.17)	(0.23)
Age	0.00	0.01	0.01	0.00***	0.00**	0.00***
	(0.92)	(1.08)	(1.41)	(2.71)	(2.62)	(2.85)
Herfindahl-Index	0.06	0.13	0.21*	0.00	0.00	0.00
	(1.13)	(1.64)	(1.95)	(0.21)	(0.33)	(0.44)
Herfindahl-Index Squared	-0.03	-0.08	-0.16*	-0.00	-0.00	-0.00
	(-0.92)	(-1.52)	(-1.94)	(-0.41)	(-0.54)	(-0.64)
Liquidity	-0.58***	-0.68***	-0.76***	0.00	0.00	0.00
	(-4.65)	(-4.90)	(-4.85)	(0.31)	(0.22)	(0.39)
Capital Expenditures	0.05**	0.07**	0.12**	0.00	-0.00	0.00
	(2.33)	(2.10)	(2.20)	(0.22)	(-0.12)	(0.04)
Leverage	0.01	0.02	0.01	0.00	0.00	0.00
	(0.84)	(1.06)	(0.76)	(1.39)	(1.48)	(1.50)
Financial Constraints	-0.01**	-0.01**	-0.01**	-0.00	-0.00	-0.00
	(-2.24)	(-2.51)	(-2.10)	(-0.60)	(-0.83)	(-0.66)
Patent Stock	-0.08***	-0.11***	-0.15***	0.00	0.00*	0.00*
	(-3.68)	(-3.06)	(-2.99)	(1.66)	(1.97)	(1.98)
Number of Employees	-0.01	-0.02	-0.02	0.00	0.00	-0.00
	(-1.60)	(-1.45)	(-1.43)	(0.02)	(0.25)	(-0.09)
Corporate Venture Capital	-0.00	-0.02	-0.03	0.00	0.00	0.01**
	(-0.06)	(-0.43)	(-0.56)	(1.08)	(1.42)	(2.29)
Observations	30,113	25,781	22,055	30,113	25,781	22,055
R-squared	0.76	0.80	0.83	0.68	0.73	0.79
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table A11 – Are Angel Employees more likely to be Founders?
This table reports the result of a linear regression examining whether angel employees are more likely to be founders. The dependent variable is an indicator variable *Founder* which takes the value of 1 if a BoardEx employee is a founder of a start-up covered in Crunchbase and 0 otherwise. The main predictor variable is *AngelEmployee* which takes the value of 1 if the director is as angel employee in our sample and 0 otherwise. *MaxQualification* is the highest degree of education attained by the executive. *Age* represents the age of the executive in 2020. *Gender* is the gender of the executive with 1 for females and 0 for males. *Achiever* is a dummy variable if the employee is associated with an achievement in BoardEx. All regressions include firm fixed effect and Year fixed effects. Heteroskedastic robust standard errors are used in the first three columns. In column 4, the standard errors are clustered by the nationality of the executive and in Column 5, we clustered the standard errors at the nationality and the company level. ***, ** and * represents significance at the 1%, 5% and 10% level, respectively. *t*-statistics are displayed in parenthesis.

	$I(Founder = 1)$	$I(Founder = 1)$	$I(Founder = 1)$	$I(Founder = 1)$	$I(Founder = 1)$
Angel Employee	-0.14***	-0.18***	-0.17***	-0.17***	-0.21*
	(-6.94)	(-6.39)	(-6.08)	(-8.25)	(-1.88)
Achiever		0.00*	0.00*	0.00	0.00
		(1.83)	(1.84)	(0.37)	(0.39)
Max Qualification			0.00**	0.00***	0.00***
			(2.02)	(5.31)	(10.28)
Age				0.00	-0.00
				(1.32)	(-1.49)
Gender				-0.01***	-0.01***
				(-16.52)	(-22.44)
Constant	0.99***	0.99***	0.99***	1.00***	1.00***
	(11,113.72)	(1,606.92)	(1,365.75)	(895.51)	(1,30.88)
Observations	832,014	258,490	248,706	109,706	7,851
R-squared	0.00	0.00	0.00	0.01	0.36
$CountryFE$	NO	NO	NO	YES	YES
$FirstCompanyFE$	NO	NO	NO	NO	YES

Figure A6 – **Model selection**

This figure visualizes model specifications as described in Brodeur et al. (2020). In order to reduce the possibility that control variables have been strategically selected, the analysis runs our baseline regression and varies which control variables are included. The number of control variables is 15, so in total, the test runs 2^{15} model specifications. The results are displayed visually. We see four graphs: 1) a t-curve with a reference line for a 5% significance level, 2) an effect size curve, 3) the distribution of t-statistics by number of controls, and 4) the distribution of effect sizes by number of controls. Differences to the baseline are due to the forced omission of Year fixed-effects. The results are similar when using different fixed effect structures.